Université de Sherbrooke
École de Gestion

# La création de valeur des données de l'Industrie 4.0 : Une étude empirique dans les manufacturiers québécois

# Data value creation of Industry 4.0 : An empirical study of Quebec's manufacturers

par
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## ABSTRACT

Manufacturing companies in developed countries face a digital transformation that is meant to improve their productivity, but also produces a large volume of data. This data will go to waste if it is not valorized by using it to gain actionable insights, for example with business intelligence and analytics. This master's thesis presents a systematic literature review and a multiple case-study on the subject of Business Intelligence in manufacturing companies. The first article, "Business Intelligence in Industry 4.0: Research opportunities", present a literature review. Results show a lack of studies on the impacts of business intelligence activities on manufacturing small and medium enterprises. The strategic impacts should be studied, since they are often neglected in favor of the operational impacts such as quality improvement and operating costs reductions. The second article, "Business intelligence value creation: A multiple case study in manufacturing SMEs", presents an exploration of the factors influencing strategic and operational business values of business intelligence. Results show the limit of the traditional models based on the Resource-Based View of the firm, which overlooks organizational factors that might be more important in smaller organizations. Contingency factors, such as organisational learning, leadership style, and the role of the owner, should be included when studying small and medium enterprises, as in these smaller organizations the lack of resources and the simpler structure affect business value of business intelligence and analytics systems differently than in larger firms. There is an interesting potential for the model suggested in this master's thesis to understand the factors linked to business value creation in smaller organization, which should be empirically tested with a larger and more diverse sample in a future study.



Keywords: Business Intelligence and Analytics, Industry 4.0, Business Value Creation, Small and Medium Enterprise.

# RÉSUMÉ

Ce mémoire présente les travaux réalisés dans le cadre de ma maîtrise en Stratégie de l'intelligence d'affaires, de l'École de Gestion de l'Université de Sherbrooke. Il consiste en deux articles. Le premier est une revue de littérature systématique ayant été soumise et acceptées à la 51$^{e}$ édition de Hawaii International Conference on System Sciences, qui a eu lieu du 3 au 6 janvier 2018. Il est présenté intégralement au chapitre deux. Le second article, présenté dans sa version longue au chapitre trois, a été soumis à la 7$^{e}$ édition de International Conference on Information Systems, Logistics and Supply Chain qui aura lieu du 8 au 10 juillet 2018. Les notices d'acceptation seront envoyées après la date de dépôt de ce mémoire. Toutes les preuves de soumissions sont présentées dans les annexes de ce mémoire. Les articles ont tous été rédigé par moi, Fanny-Ève Bordeleau, qui a également réalisé toutes les prises de données et les analyses, assistée de mes co-directeurs, les professeurs Elaine Mosconi et Luis Antonio De Santa-Eulalia.

Ce mémoire est divisé en plusieurs chapitres. Au premier chapitre, la problématique ainsi que l'énoncé des objectifs de recherche sont présentés. Dans cette introduction, j'expose que l'apport du secteur manufacturier dans le produit intérieur brut des pays développés et particulièrement au Québec a baissé de manière significative depuis l'an 2000, entre autres en raison de la montée de la concurrence internationale. Malgré tout, aux États-Unis la productivité moyenne a augmenté grâce à l'automatisation, ce qui n'est pas le cas au Québec. Dans ce contexte, plusieurs pays industrialisés ont lancé des initiatives de numérisation des entreprises manufacturières. Au Québec, le volet « Manufacturier Innovant » de la Stratégie Numérique du Québec a été lancé conjointement par Investissement Québec et le Ministère de l'Économie, de la Science et de l'Innovation. Cette étude s'inscrit dans ce contexte : alors que plusieurs manufacturiers implantent des technologies numériques, des données sont générées. La valorisation de ces données, notamment par les activités d'intelligence d'affaires, représente une opportunité importante pour les manufacturiers québécois. En particulier, les travaux de ce mémoire se concentrent sur les petites et moyennes entreprises (PME), puisque celles-ci forment la presque totalité des entreprises du secteur manufacturier québécois. L'objectif principal de ce projet est donc d'étudier les facteurs influençant la création de valeur par les activités d'intelligences d'affaires pour les PME manufacturières québécoises.

Le second chapitre présente le premier article de ce mémoire, intitulé « Business Intelligence in Industry 4.0: Research opportunities ». Il s'agit d'une revue systématique de la littérature recensant les articles et actes de conférence avec comité de révision, rédigé en anglais entre 2010 et février 2017. La recherche a été effectuée suivant la méthodologie proposée par Tranfield, Denyer et Smart (2003). Au total, 42 papiers correspondaient aux critères d'inclusion, c'est-à-dire être une étude concernant l'intelligence d'affaires ou l'analytique, dans le secteur manufacturier, et ayant trait aux transformations numériques récentes tel que l'Industrie 4.0 ou l'Internet des

Objets. Les résultats montrent la popularité croissante du sujet. De plus, un nombre important d'études se concentrent sur les architectures technologiques permettant de traiter en temps réel des données de production, ce qui n'est pas possible avec l'architecture traditionnelle en intelligence d'affaires. Une autre fraction importante des articles présente des applications d'analytique, comme de la segmentation ou des arbres de décision, sur des données de production. Le sujet étant encore récent, la plupart des articles présentent des preuves de concept donc l'impact sur les manufacturiers doit encore être démontré. Les études inclues discutent également peu des contributions de leurs recherches pour l'entreprise dans son entier et sur les aspects stratégiques, se concentrant davantage sur les aspects opérationnels.

Le troisième chapitre présente les résultats de l'étude de cas multiple auprès de six petites et moyennes entreprises québécoises. Il explore les facteurs influençant la création de valeur par les activités d'intelligence d'affaires chez les manufacturiers québécois. L'article se nomme « Business intelligence value creation: A multiple case study in manufacturing SMEs ». Les études de cas ont été réalisées en suivant un protocole tel que proposé par Yin (2009). Les cas ont été choisis pour présenter une diversité de taille d'entreprise et de secteurs industriels; il s'agit donc d'un échantillon de convenance choisi pour atteindre la saturation théorique. Six dirigeants de PME manufacturières québécoises ont été convié à une entrevue en deux parties. La première, non dirigée, consiste en une discussion sur les défis et l'environnement de l'entreprise, ces activités de traitement des données et d'intelligence d'affaires, ainsi que sa vision de la transformation numérique en cours ou à venir. Les principaux défis technologiques de l'entreprise ont également été abordés. Dans la seconde partie de l'entrevue, des questions fermées ont été posées aux dirigeants, qui étaient amené à choisir sur une échelle en cinq points la position représentant le mieux l'entreprise. Afin de mieux comprendre le contexte de l'entreprise, une discussion s'en suivait. Le modèle théorique guidant l'étude a été développé par Fink, Yogev et Even (2017), basé sur la théorie des ressources (*ressources based view*) et la théorie de la contingence (*contingency theory*). Les variables dépendantes en sont la valeur d'affaires opérationnelle de l'intelligence d'affaires ainsi que la valeur d'affaires stratégique de l'intelligence d'affaires. Les variables indépendantes de premier ordre sont l'alignement entre la haute-direction et l'équipe de technologie de l'information, l'équipe d'intelligence d'affaires ainsi que l'infrastructure technologique. Les variables de second ordre sont les capacités opérationnelles d'intelligence d'affaires et les capacités stratégiques d'intelligence d'affaires. Finalement, une variable de modération inclue dans le modèle de Fink et al. (2017) a été ajoutée : l'ambidextrie d'apprentissage organisationnel.

Les résultats suggèrent que le lien entre l'équipe d'intelligence d'affaires et les capacités stratégies d'intelligence d'affaires n'a pas pu être observé dans cette étude. Les autres liens ont pu être soulignés, malgré qu'il n'y avait cependant qu'un lien faible entre l'alignement entre la haute-direction et l'équipe des technologies de l'information et les capacités opérationnelles d'intelligence d'affaires. Le même type de lien a été observé entre l'infrastructure d'intelligence d'affaires et les capacités stratégiques d'intelligence d'affaires, ainsi qu'en les capacités opérationnelles d'intelligence d'affaires et la valeur d'affaires stratégique de l'intelligence d'affaires. Finalement, le lien de modération entre les ressources et les capacités semblent avoir un impact significatif, mais il est difficile à qualifier vue la nature de l'étude. La conclusion de cette étude est que dans le cas des PME manufacturières, les facteurs de contingence comme l'apprentissage organisationnel, le style de leadership et l'implication du propriétaire sont cruciaux pour comprendre le lien entre les ressources et les capacités en matière d'intelligence d'affaires. Finalement, le mémoire se conclu par un résumé des principaux résultats, des limites du projet de recherche ainsi que des pistes d'études futures en continuité avec les travaux de ce mémoire.  En annexe de ce mémoire se trouvent les preuves de soumissions des articles ainsi qu'un exemple du formulaire de consentement signé par tous les participants à l'étude de cas.

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# FIRST CHAPTER: RESEARCH CONTEXT AND RESEARCH PROBLEM

European and North American countries are still referred to as "industrialised countries", even though manufacturing employment has steadily declined in the last 30 years. In Quebec, between 1987 and 2000, manufacturing jobs represented between 17% and 19% of total jobs, and started declining in the 2000's, down to 12,5% in 2012 (Institut de la statistique du Québec, 2013). During the same period, manufacturing share of GDP dropped to 14,4% in 2012, after 20 years of relative stability, staying between 19% and 20% between 1984 and 2006 (STIQ, 2017). While manufacturing activities were dropping in the occidental world and rising in emergent and low-cost countries such as China, technological advances opened automatization opportunities for increasingly intelligent tasks (Zhang, Peek, Pikas, & Lee, 2016). These advances were considered to counterbalance the delocalisation of manufacturing, as they allowed for better, faster and cheaper production with less workers (Dews, 2017). Hence, manufacturing productivity in the United States raised between 1980 where 25 workers were needed to produce 1 million dollars manufactured goods, to 2016 where only 6,5 workers are needed for the equivalent 1 million dollars (Dews, 2017). In this context, several countries launched national reindustrialisation through integrated automation production programs, the most notable being Germany's "Industrie 4.0" (Industry 4.0 in English) (Kagermann, Wahlster, & Helbug, 2013). Several countries followed this digital transformation trend. In Quebec, the government launched in 2016 a "Digital Strategy", including an "Innovative manufacturer" chapter. These programs, which included funding for manufacturing small and medium enterprises (SMEs), aimed at promoting various digital technologies and supporting manufacturers in their implementation, in the hope of increasing the province's manufacturing productivity (Ministère de l'Économie, de la Science et de l'Innovation, 2016).

Introducing these new technologies in factories generates large amounts of data and opens new performance monitoring possibilities, such as the automatic generation of real-time performance indicators (Bagheri, Yang, Kao, & Lee, 2015a). Traditional performance monitoring is not enough to keep up with this rapidly changing situation; this is where business intelligence and analytics (BI&A) comes into action (Eckerson, 2011). BI&A is an information systems approach helping companies make better business decisions and take better actions through the acquisition of data, analysis of information, and dissemination of knowledge (Eckerson, 2011). In recent years, operational manufacturing BI&A has emerged as a way to valorize real-time production data by contributing to decision-making (Hänel & Felden, 2013).

Using BI&A helps a manufacturer improve its processes, but value creation, including increased productivity, is not guaranteed by the simple implementation of a technology (Ross, Beath, & Goodhue, 1996). Past studies have shown that a strong IT team to support the technology and buy-in from the managers are prerequisite to performance (Elbashir, Collier, & Davern, 2008; Ross et al., 1996). While many studies were made on the vast subject of BI&A project success or the link between technology and business performance (Elbashir et al., 2008; Fink, Yogev, & Even, 2017), few have adapted their models to manufacturing SMEs.

SMEs account for 99% percent of Quebec manufacturing companies (STIQ, 2017). These smaller businesses are less likely to have a formal technological governance structure and a smaller IT team, if any, to support users (Garengo, Biazzo, & Bititci, 2005). Their owner is often more involved in management and daily operations (Raymond, Marchand, St-Pierre, Cadieux, & Labelle, 2013). Finally, they are more limited in their financial resources and thus have more difficulties building and maintaining the complex technological architecture need to exploit connected equipment and analytical algorithms (Garengo et al., 2005).

In this context, this study aims first at getting an in depth understanding of the valorization of data in the emergent technological revolution phenomenon known as Industry 4.0, specifically in SMEs; and second at exploring factors linked to business value generation from BI&A activities in manufacturing SMEs. This exploration will support SMEs in their technology development strategy and will give them base rules to ensure they reap benefits from their investments. In this project, whenever possible we base our evaluation of data on existing theory and empirical data objectively evaluated, complemented with interpretation of the qualitative data. The research objectives are as followed.

Second chapter: explore the literature on business intelligence related to Industry 4.0 to identify research gaps and opportunities and the place of value creation or success measurement in the literature.

Third chapter: explore the factors linked to business value generation from BI&A activities in manufacturing SMEs, based on a BI&A value creation model empirically validated in larger companies (Fink et al., 2017).

These two chapters consist of articles submitted to conferences as described in the forewords of the second and third chapters. The article presented in the second chapter consist of a systematic literature review while the article presented in the third chapter is a multiple case study.

# SECOND CHAPTER: BUSINESS INTELLIGENCE IN INDUSTRY 4.0: RESEARCH OPPORTUNITIES

## 1. FOREWORD

This article was submitted on June 15th for the 51rs Hawaii International Conference on System Sciences. It was accepted, and presented on January 6th, 2018, in Waikoloa, Hawaii. The research and redaction were made by me, Fanny-Ève Bordeleau, with support of my co-directors Elaine Mosconi and Luis Antonio de Santa-Eulalia. Proof of submission can be found in the appendices. Full reference: Bordeleau, F.-E., Mosconi, E., & Santa-Eulalia, L. A. (2018). Business Intelligence in Industry 4.0: State of the art and research opportunities. In *Proceedings of the 2018 51th Hawaii International Conference on System Sciences (HICSS)*. 3944-3953. Waikoloa, Hawaii. ISBN: 978-0-9981331-1-9

## 2. ABSTRACT

Data collection and analysis have been at the core of business intelligence (BI) for many years, but traditional BI&A must be adapted for the large volume of data coming from Industry 4.0 (I4.0) technologies. They generate large amounts of data that need to be processed and used in decision-making to generate value for the companies. Value generation of I4.0 through data analysis and integration into strategic and operational activities is still a new research topic. This study uses a systematic literature review with two objectives in mind: understanding value creation through BI&A in the context of I4.0 and identifying the main research contributions and gaps. Results show most studies focus on real-time applications and integration of voluminous and unstructured data. For business research, more is needed on business model transformation, methodologies to manage technological implementation, and frameworks to guide human resources training.

# 3. INTRODUCTION

Business intelligence has been improving the decision-making process in a variety of contexts for years (Fink et al., 2017). The discipline is likely to be transformed in the wake of the fourth Industrial Revolution.

This fourth Industrial Revolution is currently underway (Schwab, 2016), as acknowledged by the World Economic Forum in their annual meeting of 2016. Scientists from around the globe are dedicating resources to studying its impact on manufacturing companies. Some studies (Bagheri, Yang, Kao, & Lee, 2015b; Dai et al., 2012; Gröger et al., 2016; J. Lee, Bagheri, & Kao, 2015), cite economic factors, including fierce competition, as the leading reason to understand these changes. Technological drivers, such as product complexity (Eiskop, Snatkin, Kõrgesaar, & Søren, 2014), come second, followed by social factors, especially end consumers' changing requests (Eiskop et al., 2014) and mass customization (Neuböck & Schrefl, 2015).

The smart factory of Industry 4.0 generates a large volume of industrial data at a great speed. The recent increase in availability of sensors and acquisition systems has sparked interest in Cyber-Physical Systems applications (J. Lee et al., 2015), but the value creation coming from the usage of data has not received the same attention, as will be shown in this review. To ensure data can be converted to valuable insights, it needs to be integrated and analyzed, ideally in an automated fashion, to reduce manual work (Hänel & Felden, 2016). In this context, manufacturing companies have turned to data analysis to improve their decision-making processes (Jay Lee, Kao, & Yang, 2014). Some companies chose to analyze maintenance related data to decrease the operating cost, while other reinvent their business model by selling data analysis on top of their conventional products. No matter how they chose to valorize data, to be able to face the harsh competitive and economic environment, this usage of data will need to lead to improved business performance.

In this paper, we are seeking to understand which aspects of business intelligence and data analysis can lead manufacturing companies to value creation, and to identify the main research contributions and gaps in BI&A literature on Industry 4.0. To this end, we have conducted a systematic literature review of business intelligence literature in the context of the fourth Industrial Revolution. Four databases, representing the main publications in business and engineering, were searched. Results show a great proportion of studies focus on real-time applications and integration of voluminous and unstructured data. They also highlight gaps in business related aspects, such as value creation or business model transformation, with most studies focusing on the technical aspects of Industry 4.0.

This paper is organized as follows. The next section provides the general research background. Subsequent sections detail the methodology, list the results of the systematic literature review, discuss the key findings and highlights the direction for further research.

## 4. RESEARCH BACKGROUND

### 4.1. Business intelligence

Business intelligence (BI) is a broad concept including the collection, integration, analysis and visualization of organizational data to support and improve the decision-making process (Fink et al., 2017). The phases of a BI&A initiative adapted from Eckerson (Eckerson, 2011) are presented in Figure 1. First, data is collected. Then, it is extracted, transformed and loaded (ETL) into the multidimensional database, usually a Data Warehouse, where it can be analyzed and presented (Eckerson, 2011). Data presentation includes reports and interactive data discovery (Hänel & Felden, 2016), alerts and operational graphical user interface (Eiskop et al., 2014) or dashboards (Groger & Stach, 2014; Hänel & Felden, 2016). These phases rely on a technical architecture, often including a data warehouse.

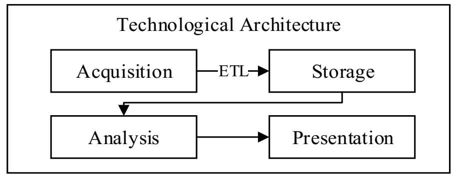


Figure 1. Phases of BI, adapted from Eckerson (2011)

The benefits of BI&A are mostly indirect. BI&A contributes to fact-based decision-making and helps improve the quality of information (Fink et al., 2017). These improved decisions based on quality information then lead to enhanced business performance. On the other end, the technological improvements and new Cyber-Physical Systems offer new BI&A capabilities, such as predictive and adaptive indicators (Bagheri et al., 2015a) which were not previously measurable. They can also facilitate and reduce the cost of real-time operational dashboards (Eiskop et al., 2014), a technology previously available but complex and cost-prohibitive.

### 4.2. BI&A operational and strategic value creation

BI&A can be used at any hierarchical level in the company: strategic, tactical or operational (Eckerson, 2011). This paper will focus on the strategic and operational levels, leaving aside the tactical level which can sometimes be harder to distinguish from the other two. At the operational level, BI&A serves workers by monitoring processes (Eckerson, 2011), often with the help of performance indicators. At the strategic level, executives monitor, manage, and analyze business performance in accordance with the strategic objectives (Eckerson, 2011). Strategic objectives supported by BI&A include new market development, major manufacturing technological investments or modifications to business models. Operational and strategic value are captured differently. Fink et al. (2017) state that "operational value represents improvements in the efficiency of business process […] whereas strategic value represents the ability to meet organizational objectives" (p.44). Manufacturing applications of BI, sometimes referred to as Manufacturing Intelligence (Hänel & Felden, 2016), are often more operational in nature since they aim at improving floor plant decisions. Real time monitoring and analysis are two of the most popular applications, but this does not negate the use of operational information to improve business decision on a strategic level, such as competition related questions.

Operational BI&A capabilities are strongly related to operational value creation, but also lead to strategic value creation (Fink et al., 2017). Thus, companies should dedicate resources to measuring strategic value even when only operational BI&A applications are implemented. This measure will contribute to situation awareness with respect to the execution of the business plan, and facilitate the business's transition into Industry 4.0.

### 4.3. Industry 4.0 and the Smart Factory

Industry 4.0 is a concept introduced by the German government to lead manufacturing companies into the fourth Industrial Revolution (Jay Lee et al., 2014). The core technologies of Industry 4.0 include sensors, communication protocols, cloud computing, cyber-physical systems, additive manufacturing, business intelligence and big data, and other emerging technologies. Most of these technologies are not recent innovations. However, it is the combination of technologies, business processes, and data processing that makes Industry 4.0 a novelty (Anderl & Fleischer, 2015). Schwab (Schwab, 2016) expressed the need to understand how the fourth Industrial Revolution will reshape the "economic, social, cultural and human context in which we live" (p.2). Value creation for organizations will be achieved through innovative products and services, increased competitiveness and improved operational processes (Anderl & Fleischer, 2015). Although Industry 4.0 is only one of many government led initiatives to guide companies through the current revolution, this paper uses it as a guideline because of the prevalence of the term in academic literature. Possible synonyms include smart manufacturing, the industrial internet and the smart factory.

Industry 4.0 manifests itself in many ways, the most prominent being the smart factory. A smart factory integrates autonomous computing and machine-to-machine communication to achieve a state of self-awareness and create self-learning machines (Jay Lee et al., 2014). This allows for better control of manufacturing processes, such as monitoring the remaining useful life of tools and equipment, increased uptime and better product quality (Bagheri et al., 2015a), providing we can collect, analyze and use the data.

### 4.4. Reference Architecture: RAMI4.0

Since Industry 4.0 is a new concept, there is a need to develop a shared language and a structured framework. The Reference Architectural Model of Industry 4.0 (RAMI 4.0) is a three-dimensional model developed by a consortium led by the Association of German Engineers (VDI) and German Electrical and Electronic Manufacturers' Association (ZVEI) (Adolphs & Epple, 2017). It is intended to assemble Industry 4.0 related standards. Figure 2 below is reproduced from Adolphs and Epple (Adolphs & Epple, 2017). The cube is meant to represent horizontal integration of data in the value stream and vertical integration through an enterprise's hierarchical levels: product, field device, control device, station, work center, enterprise, and the connected world.

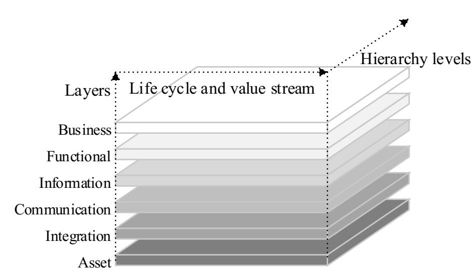


Figure 2. RAMI 4.0, adapted from Adolphs and Epple (2017)

The layers are meant as a reminder to integrate all aspects of the enterprise in the digitalization, not only communication and information. For instance, a successful business intelligence application like a team leader's dashboard must integrate and compute data coming from assets such as equipment's sensors, communicate it to the dashboard and meet the requirements of the business layer, namely the business's senior management.

# 5. Research method

To minimize bias in the selection of the articles included in this study, a systematic methodology was adopted. A systematic review is a transparent and reproducible search of the existing literature, in which great care is taken to apply objective criteria to the inclusion or rejection of an article (Tranfield, Denyer, & Smart, 2003). Transparency and reproducibility is ensured by following the guidelines proposed by Tranfield, Denyer and Smart (Tranfield et al., 2003). These guidelines consist of nine phases divided in three stages, as presented in Table 1.

Table 1. Stages of a systematic review, adapted from Tranfield et al. (Tranfield et al., 2003)

| **Stage** | **Phase** |
|---|---|
| **1. Planning the review** | |
| | 0. Identification of the need for a review |
| | 1. Preparation of a proposal |
| | 2. Development of review protocol |
| **2. Conducting the review** | |
| | 3. Identification of studies |
| | 4. Selection of studies |
| | 5. Study quality assessment |
| | 6. Data extraction |
| | 7. Data synthesis |
| **3. Reporting the results** | |
| | 8. Report and recommendations |
| | 9. Getting evidence into practice |

## 5.1. Planning the review

As previously mentioned in this paper, Industry 4.0 is still a relatively new subject in academic literature and there are gaps in business intelligence research on the subject. Thus, there is a need to grasp what has been investigated and what remains to be studied. We are especially interested in existing studies' mentions of value creation, operational and strategic. While developing the review proposal, the existing literature was searched. No other literature review on BI&A and Industry 4.0 was available at this time. The review protocol (Tranfield et al., 2003) included identification of the research question, the search criteria including dates and databanks to be searched, and the inclusion criteria. The protocol summary is presented in Table 2. More details are given in the following section.

Table 2. Review protocol summary

| | |
|---|---|
| **Subject** | Business intelligence in manufacturing in Industry 4.0 |
| **Research questions** | What are the gaps and research opportunities in business intelligence regarding Industry 4.0 for manufacturing? Which aspects of business intelligence and data analysis can lead manufacturing companies to value creation? |
| **Dates** | from 2010 to extraction date (February 2017) |
| **Databanks** | ABI/Inform, Business Search Complete, ScienceDirect, Scopus |
| **Search criteria** | Peer reviewed; Academic literature; Full text included; English;<br>Title, abstract and keywords OR All (except full text) |
| **Inclusion criteria** | Discusses at least one manufacturing activity in the following list: matter transformation, equipment maintenance, plant warehouse management or explicit mention of manufacturing AND Discusses at least one BI subject in the following list: decision making process or decision support (including data acquisi-tion and storage), data quality, information display, performance monitoring, analytic or data analysis |
| **Keywords (I4.0)** | Industry 4.0, Industrie 4.0, Smart factory, Manufacturing intelligence, Industrial internet |
| **Keywords (BI)** | Business intelligence, BI, Analytics, Data analysis, Data science, Monitoring, Surveillance, MES, Manufacturing execution system, SCADA, Supervisory Control And Data Acquisition |

### 5.2. Conducting the review

The objective of this review is to identify studies that were conducted in the field, and determine any gaps and opportunities in business intelligence research in Industry 4.0, specifically those related to manufacturing. It consists of a systematic examination of peer reviewed and indexed scholarly articles or conference papers published between 2010 and January 2017 on the above-mentioned topics. The year 2010 was chosen as the earliest date since the Industry 4.0 concept was defined in Germany around 2011. The first architectural reference model for Industry 4.0 was published in 2015 (Adolphs & Epple, 2017) and was accepted as a standard by German standard association DIN in 2016.

The following keywords were used as synonymous for Industry 4.0: Industry 4.0, Industrie 4.0, smart factory, manufacturing intelligence, and industrial internet. The keywords related to business intelligence were: business intelligence, analytics, data analysis, data science, monitoring, surveillance, MES, manufacturing execution system, SCADA, supervisory control and data acquisition. Four electronic article databases were selected because they contain the main publications in business intelligence and information systems: ABI/Inform, Science Direct, SCOPUS and Business Source Complete. Whenever possible, the search was limited to the title, abstract or keywords. If this option was not available, the search was set to “all except full text”. Only English publications were included.

To be included in the sample, the article had to correspond to the definition of BI&A as presented in section 4.1, notably the project had to deal with treating useful information, and not just raw data. It also had to cover manufacturing operations, or manufacturing companies. Value creation was not considered an inclusion criterion since a sub-goal of this study is to determine to what extent the value creation is included in the articles.

The search yielded 299 publications which were exported to eliminate duplicates. They were then filtered first on abstract reading, and finally for a complete reading based on the inclusion criterion mentioned above. The study quality assessment was made during the complete reading. No articles were excluded based on the quality of the research method. Table 3 presents the filtering results, with 42 distinct articles fitting the inclusion criterion. Most of the rejected articles were excluded because they were focusing on very technical aspects, i.e. wireless communication protocol, database structure or design of new sensors. They were not considered BI&A research.

A backward search was only performed when necessary to understand the context of an article, and was not included in the studied publications.

Table 3. Articles filtering process

| **Filtering stage** | **Articles count** | | |
|---|---|---|---|
| Database extract | 299 | | |
| ABI/Inform:10 | Science Direct: 44 | SCOPUS: 185 | Business Source Complete 60 |
| Duplicate removal | 248 | | |
| Abstract reading | 97 | | |
| Full article reading | 42 | | |

During the reading of the full article, various information on the article's bibliometrics and content was tagged for analysis based on the research design, BI&A subject, RAMI4.0 layer, cited performance indicators and value creation measures or indicators. The results are presented in section 6.

# 6. Results

## 6.1. Bibliometric analysis

The bibliometric analysis is based on five criteria: year of publication, journal or conference, authors, country of the principal author, and research design.

The distribution by publication year is detailed in Figure 3. Although the year filter was set to 2010, the earliest relevant articles were published in 2012. This is consistent with the emergence date of Industry 4.0. Interest in the subject seems to be growing significantly, although it should be noted that, for 2017, only January was included in the study.

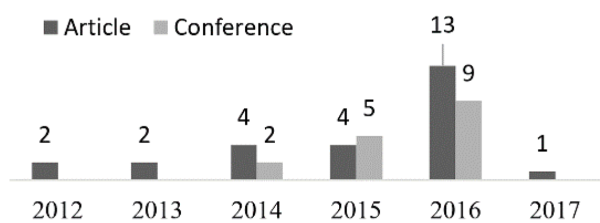


Figure 3. Distribution by publication year

A significant number of articles were conference proceedings. The 42 articles were distributed in 30 publication channel, journals or conferences. Three publication channels had at least three articles: ten articles were published through one of IEEE's channels, five were published in the conference proceedings of CIRP and three in the proceedings of the International Federation of Automatic Control. The Industry 4.0 concept originally comes from Germany. Unsurprisingly, almost a quarter of the selected articles were published there.

A clear majority of articles presented the creation of a physical or digital artefact, such as a database infrastructure or the programming of a dashboard. Some authors employed a conceptual design, notably in Cyber-Physical Systems architecture (Bagheri et al., 2015a; J. Lee et al., 2015).

### 6.2. Content analysis

Analysis of BI&A and related technological aspect reveals 33 out of 42 articles included real time or near real-time data processing. In many of these articles, authors emphasized the technical difficulty of processing machine data in real time, because of database limitations (Brandenburger et al., 2016), the integration of unstructured data (Kassner & Mitschang, 2015), limits to the acceptable visual complexity (Xu, Mei, Ren, & Chen, 2017) or the number of variables required to develop a sufficiently precise model, (Wuest, Irgens, & Thoben, 2014).

Nearly half of the articles presented data analysis applications, such as clustering (Bagheri et al., 2015a; Wuest et al., 2014) or decision trees (Chien, Hsu, & Chen, 2013a). Figure 4 also shows 16 articles suggested a technological architecture without focusing on a single BI&A phase. For example, a technological framework using real-time employee localization to adjust information display on a dashboard, which covers data acquisition, storage, analysis and presentation (Khaleel et al., 2015).

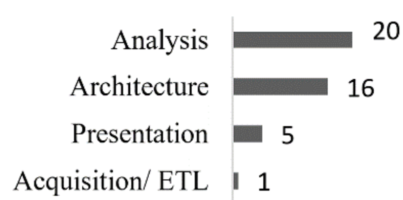


Figure 4. BI&A subject distribution

The classical BI&A architecture, relying on a data warehouse, cannot alone process unstructured or voluminous data in real or near real time (Biswas & Sen, 2016). Several authors have mentioned using Manufacturing Execution Systems (MES) to integrate data coming from different machines, devices and products (Eiskop et al., 2014; Gröger et al., 2016; Hänel & Felden, 2016) in real time. Data collected by the MES can then be used to feed dashboards, control cards or statistical algorithms.

Only three articles address the specific needs of Small and Medium-Sized Enterprises (SME). These companies often have limited financial and technological resources, and adopting a complete BI&A infrastructure is beyond their reach (Dai et al., 2012). Several industrial domains were covered, notably aluminium (Cao, Wang, Shi, & Yin, 2015), steel rolling (Hänel & Felden, 2016) and flat steel (Brandenburger et al., 2016), automotive parts (Dai et al., 2012), equipment manufacturing (Nino, Blanco, & Illarramendi, 2015) and maintenance (Yu, Lin, & Chien, 2014). Strategic value creation measurement is underrepresented in the sample studies, being addressed in only three articles as shown in Table 4.

Table 4. Measure of value creation by BI&A in Industry 4.0 context

| **Authors** | **Operational value** | **Strategic value** | **Method** |
|---|---|---|---|
| Brandenburger et al. (Brandenburger et al., 2016) | Rework reduction, cost reduction, improved yield and improved quality | n/a | Proof of concept |
| Chen et al. (Y.-J. Chen, Fan, & Chang, 2016) | Reduced false alarms, improved catch rate (quality measurements) | n/a | Proof of concept |
| Chien et al. (Chien, Hsu, & Chen, 2013b) | Improved quality of operational decision-making | n/a | Proof of concept |
| Chien et al. (Chien et al., 2013a) | Improved efficiency by controlling process variations, improved quality | n/a | Proof of concept |
| Chien et al. (Chien, Diaz, & Lan, 2014) | Reduced material usage, reduced scrap, improved productivity | n/a | Proof of concept |
| Dai et al. (Dai et al., 2012) | Improved production efficiency, quality, and timeliness of information, reduced paperwork, operational errors, and work in progress inventories | Improved annual input, reduces global costs and managerial partiality, increase sales, improved reputation | Proof of concept |
| Eiskop et al. (Eiskop et al., 2014) | Improved productivity | n/a | Proof of concept |
| Engeler et al. (Engeler, Treyer, Zogg, Wegener, & Kunz, 2016) | Reduced downtime, improved ease of use, improved data detail | n/a | Interviews |
| Gröger et al. (Gröger et al., 2016) | Keeping human in the loop, learning organisation | n/a | Proof of concept |
| Hänel & Felden (Hänel & Felden, 2016) | Increased efficiency by reducing time to get data and improved data quality, improved awareness and data precision | n/a | Proof of concept and interviews |

| Authors | Operational value | Strategic value | Method |
|---|---|---|---|
| Kao et al. (Kao, Chang, Dauzere-Peres, & Blue, 2016) | Improved predictive overall equipment effectiveness (OEE) | n/a | Proof of concept |
| Lee et al. (C. K. M. Lee, Yeung, & Cheng, 2016) | Reduced cost by economies of scale | Reduced carbon footprint | Proof of concept |
| Lee et al. (Jay Lee et al., 2014) | Improved prediction of remaining useful life | n/a | Proof of concept |
| Neuböck & Schrefl (Neuböck & Schrefl, 2015) | Improved agility by reacting more quickly to change in orders | n/a | Proof of concept |
| Niño et al. (Nino et al., 2015) | Reduced waste, improved return on production process | n/a | Proof of concept |
| Oneto et al. (Oneto, Anguita, Coraddu, Cleophas, & Xepapa, 2016) | Improved accuracy of data model | n/a | Proof of concept |
| Oses et al. (Oses, Legarretaetxebarria, Quartulli, García, & Serrano, 2016) | Improved prediction of energy savings | n/a | Proof of concept |
| Shafiq et al. (Shafiq, Velez, Toro, Sanin, & Szczerbicki, 2016) | Maintain just-in-time maintenance, improved asset utilization, improved flexibility | n/a | Proof of concept |
| Tervonen et al. (Tervonen, Isoherranen, & Heikkila, 2015) | Improved data quality | Boost new business models, improved current product, create new products | Proof of concept |
| Xu et al. (Xu et al., 2017) | Improved ease of use and perceived usefulness of information, inefficiencies uncovered | n/a | Interviews |

Table 4 presents the 20 articles out of 42 mentioning operational value, strategic value or both. Operational value creation is measured in 20 articles. It is possible to assess BI&A value creation either objectively, i.e. by measuring the variation of a specific performance indicator over time, or subjectively, by interviewing users and managers. Objectives measurements were preferred in the majority of the articles. Most articles note better product or process quality after the BI&A project was implemented. Other benefits included reduced operating or maintenance costs, improved efficiency and increased data quality. The strategic benefits mentioned are increased sales, improved reputation, enhanced product quality and access to new business models. The favored method of success validation in the sampled articles is a proof of concept, where the project is implemented and the results assessed. Interviews were also used to measure the value created from the BI&A project, especially when the authors wanted to emphasize qualitative gains such as perceived ease of use (Engeler et al., 2016; Xu et al., 2017) and perceived data quality (Hänel & Felden, 2016).

A common and objective way to assess operational value creation is to measure the variation of performance indicators. Figure 5 shows that the most popular indicators in the studied articles are quality rate, various cost reductions, production efficiency and uptime and yield. Indicators are classified according to the four perspective (Kaplan & Norton, 1996), excluding learning and growth for which no indicators were cited in the sample. Most indicators relate to the processes.

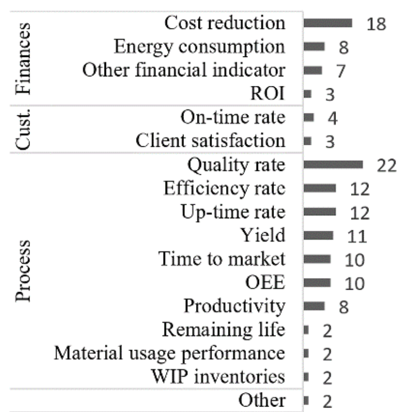


Figure 5. Cited performance indicators

The composite indicator overall equipment effectiveness (OEE) is cited in almost a quarter of all articles. Productivity is only cited in eight articles, despite being a common performance measure in operations management.

Table 5. Articles description

| Authors | Description | Cited gaps or limits | RAMI4.0 layer |
|---|---|---|---|
| Bagheri et al. (Bagheri et al., 2015b) | Adaptive clustering for self-adjusting machines | n/a | n/a |
| Biswas & Sen (Biswas & Sen, 2016) | Propose a supply chain architecture for classical and big data based analytics | Need to adapt communication protocol based on application | Information |
| Brandenburger et al. (Brandenburger et al., 2016) | Analytics for visual quality monitoring in flat steel production | Limited by existing database infrastructure | Integration |

| Authors | Description | Cited gaps or limits | RAMI4.0 layer |
|---|---|---|---|
| Cao et al. (Cao et al., 2015) | Architecture for production monitoring in aluminum industry | Need to validate in practice | Functional |
| Chen Y et al. (Y. Chen, Lee, Shu, & Crespi, 2016) | Propose guidelines for collaborative sensing intelligence | Several issues to be addressed: data integration, mining, real time algorithm development, etc. | Information |
| Chen Y-J. et al. (Y.-J. Chen et al., 2016) | Analytics for reduction of false positive in defect detection | Room for model further improvement | Information |
| Chien C-F et al. (Chien et al., 2014) | Data mining for production process improvement | Room for model further improvement | Information |
| Chien C-F et al. (Chien et al., 2013a) | Detection and classification of defects for yield enhancement | Improve model to account for more variables | Information |
| Chien C-F et al. (Chien et al., 2013b) | Real time identification and classification of manufacturing defects | Room to improve with a larger data set | Information |
| Dai et al. (Dai et al., 2012) | Case study of RFID real-time tracking in a shop floor | n/a | n/a |
| Eiskop et al. (Eiskop et al., 2014) | Production monitoring system architecture adapted for SME | Needs to be tested in a manufacturing environment | Functional |
| Engeler et al. (Engeler et al., 2016) | Comparison of model based and statistical based condition monitoring | Large scale validation to be done | Functional |
| Fleischmann et al. (Hans Fleischmann, Kohl, & Franke, 2016) | Architecture for machine condition monitoring to lower workers' cognitive overload | n/a | n/a |
| Fleischmann et al. (H. Fleischmann, Kohl, & Franke, 2016) | Architecture for socio-cyber-physical systems in machine condition monitoring | n/a | n/a |
| Gröger & Stach (Groger & Stach, 2014) | Real time mobile dashboard for manufacturing | n/a | n/a |
| Gröger et al. (Gröger et al., 2016) | Architecture for a data-driven factory and application scenarios | Need to investigate the resulting competitive advantage | Business |
| Hänel & Felden (Hänel & Felden, 2016) | Architecture for real time operational BI | Need further evaluation and examples to be generalized | Functional |
| Kao et al. (Kao et al., 2016) | Introduce predictive indicator for plant performance | n/a | n/a |
| Kassner & Mitschang (Kassner & Mitschang, 2015) | Integration of unstructured data in exception handling architecture | Complexity of integrating unstructured data in real time | Integration |
| Khaleel et al. (Khaleel et al., 2015) | Various industrial IoT applications examples and related frameworks | n/a | n/a |
| Lee et al. (C. K. M. Lee et al., 2016) | Architecture for big data analysis including external data | n/a | n/a |
| Lee. et al. (Jay Lee et al., 2014) | Analysis of readiness of predictive tool for manufacturing services transformation | n/a | n/a |
| Lee et al. (J. Lee et al., 2015) | Propose a cyber-physical system architecture in 5 layers | n/a | n/a |

| Authors | Description | Cited gaps or limits | RAMI4.0 layer |
|---|---|---|---|
| Lee et al. (H. Lee, Yoo, & Kim, 2016) | Architecture for efficient energy management | n/a | n/a |
| Lee R. et al. (R. Lee, Chen, & Nichols, 2016) | Lit. review on knowledge management in smart factory | n/a | n/a |
| Leitão et al. (Leitão, Barbosa, Pereira, Barata, & Colombo, 2016) | High level architecture for smart factory | n/a | n/a |
| Miškuf & Zolotova (Miškuf & Zolotová, 2015) | Case study on data exploration software implementation | n/a | n/a |
| Neuböck & Schrefl (Neuböck & Schrefl, 2015) | Dimensional modelling applied to material planning | n/a | n/a |
| Niño et al. (Nino et al., 2015) | Pilot study of equipment data real-time analysis | Ongoing; needs to be extended | Functional |
| Oneto et al. (Oneto et al., 2016) | Data driven model for vessel monitoring state prediction | n/a | n/a |
| Oses et al. [35] | Reduction of the range of prediction interval in energy savings measurement | Need to include more factors for better prediction | Information |
| Park (Park, 2016) | Success factors and expected effects of connected factory | n/a | n/a |
| Rix et al. (Rix, Kujat, Meisen, & Jeschke, 2016) | Framework for die casting real time monitoring | Need to link information company wide | Business |
| Shafiq et al. (Shafiq et al., 2016) | Present a technical framework for an intelligent factory | n/a | n/a |
| Ternoven & Heikkilä (Tervonen et al., 2015) | Literature review on data mining and analysis in IIoT | Include social networking and human interactions in DM | Business |
| Wang H. et al. (H. Wang et al., 2016) | Framework for big data analysis and ship monitoring | n/a | n/a |
| Wang S. et al. (S. Wang, Wan, Li, & Zhang, 2016) | Description and application of a smart factory; RFID tracking demonstration | Technical challenges to the smart factory implementation | Asset |
| Wieland et al. (Wieland et al., 2016) | Low cost and flexible ruled-based assistant for manufacturing | Need to implement and evaluate - | Functional |
| Wuest et al. (Wuest et al., 2014) | Machine learning clustering to monitor manufacturing quality | Need to include all known parameters; complex model | Information |
| Xu et al. (Xu et al., 2017) | Real time visual assembly line performance analysis by adapting Marey's graph | Limits to the complexity of data that can be displayed | Information |
| Yoon et al. (Yoon, Shin, & Suh, 2012) | Technical architecture and requirements for a Smart Factory | n/a | n/a |
| Yu et al. (Yu et al., 2014) | Automated real time equipment monitoring | Need to further examine practical viability | Functional |

Among the authors who mentioned value creation, four had the objective of making the necessary information available or more easily accessible, and four others mentioned changes in processes at a higher level. As shown in Figure 6, most articles had the goal of improving the function of the asset being worked on. No articles only covered communication, integration or assets in the articles mentioning value creation. Table 5 above provides a brief description of each selected article and its covered RAMI corresponding layer.

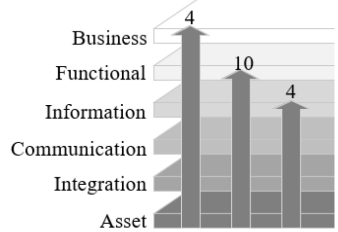


Figure 6. Architecture layer distribution

## 7. Discussion and conclusion

This study pointed out research gaps and opportunities in Industry 4.0's literature on business intelligence regarding business related issues such as value creation. A total of 42 articles were identified through a systematic literature review. Results show real-time monitoring and analysis were the most common BI&A phases, followed closely by architecture, but very few articles referred to the operational or strategic value of BI&A applications.

Although authors included in this review cited global competition and increasingly demanding customers as drivers for the implementation of Industry 4.0 projects, most failed to demonstrate how their projects helped companies reach their strategic objectives. Industry 4.0 relies on disruptive innovations and changes in business models and aims to offer companies a competitive edge in a world where consumers are looking for quality and customization while preserving mass production costs and delays (Schwab, 2016). However, only one author referred to new business model improvements (Tervonen et al., 2015). Furthermore, as demonstrated in the previous section, BI&A research in Industry 4.0 has focused primarily on operational capabilities and has mostly measured operational value creation. Performance indicators such as quality rate and costs reduction are the most common measures of operational value in the cited articles. Strategic value for a company can be influenced by better operational capabilities (Fink et al., 2017), but we need to demonstrate the link between the project and the company's goals.

A possible explanation for the lack of value creation measurement is that research in the field is currently led by technically-focused engineering schools, opening up opportunities for business intelligence researchers. Several authors mention that there is still a need to validate their concept in a real manufacturing setting, implying the project was not based on a specific company and its strategic planning.

Overall, the bibliometric analysis shows a rising interest in business intelligence in the wake of the various Industry 4.0 related initiatives, especially in countries where the manufacturing sector represents a large proportion of GDP. The most common research methodology is design science research, showing that research in business intelligence adapted to Industry 4.0 is still diverging on new concepts, but there are also opportunities for confirmatory research.

Out of 42 articles, 33 included usage of data on a real or near-real-time basis. This is consistent with the smart factory concept, where the product, machine, building, and workers exchange data continuously. However, the benefits of real-time data analysis or monitoring have yet to be demonstrated, since few papers provided objective results. This integration of data along the hierarchical axis of RAMI 4.0 is well covered in the selected literature. However, only a handful of articles mention the importance of communicating information through all layers of the company, up to the business level, in to order to adapt the processes. This point will need to be corrected to ensure companies can validate value creation for the entire company and not just for the manufacturing function.

Technological limitations such as insufficient database infrastructure (Brandenburger et al., 2016) or the complexity of integrating real time data (Kassner

& Mitschang, 2015) were cited by some authors as limitations in data integration and analysis in manufacturing processes. This is reflected in the number of articles focusing on the proposition of a standardized manufacturing BI&A architecture capable of real-time analysis. Several frameworks have been suggested, expanding on the classical BI&A architecture to include voluminous and unstructured data. However, most articles mention the need for extensive testing on their proposed architecture. They also need to integrate information with all layers of the enterprise, as suggested in RAMI 4.0.

This study identified several gaps or research opportunities in BI&A literature focusing on manufacturing and Industry 4.0. Notably, there is a need to evaluate the various developed architectures, their differences and common features, and suggest and validate a unified technological architecture for BI&A in Industry 4.0, one which is usable in different contexts. Another research opportunity is the confirmation of value creation for companies in the integration and analysis of real-time manufacturing data. Similarly, unstructured or voluminous data are gaining in popularity in manufacturing, but research on the subject remains anecdotal. Yet another subject to be covered is the validation of the value creation measures, notably performance indicators, to ensure those used in the academic literature are representative of the one used in practice. Finally, to achieve the goals of augmented competitive advantage through Industry 4.0 concepts, innovative projects are underway, both in the corporate world and in academia. Most of the selected articles did not mention innovation management capabilities or organization learning in manufacturing companies; many aspects remain to be studied, including the impact of Industry 4.0 technological projects on organizations with various dominant organisational learning mode.

At the moment, based on the literature, it is not possible to generalize about the value for the business created by BI&A applications in Industry 4.0, considering the lack of success measure in the selected articles. There is a need for a value creation framework adapted to BI&A and manufacturing in a context of rapid technological changes. This framework should include both objective measures of success such as performance indicator variations, and subjective measures such as perceived success. It should also include measurement of strategic value creation, to ensure companies achieve their strategic objectives. This suggests opportunities for future empirical and longitudinal studies.

There are limitations to this research. Several articles were excluded because they only covered technical aspects of data collection, such as sensor development or communication protocols, and, thus, did not meet the inclusion criterion. Furthermore, only English publications were included. As the subject is still emergent, publications were selected from several sources, including smaller conferences. This diversity made comparison of the articles' structure and quality more complex. A further improvement would be to analyse articles based on tactical or managerial levels, in addition to operational and strategic levels. Future work will focus on the business intelligence aspects of value creation through the use of BI&A in Industry 4.0 projects.

# THIRD CHAPTER: BUSINESS INTELLIGENCE VALUE CREATION: A MULTIPLE CASE STUDY IN MANUFACTURING SMES

## 1. FOREWORD

This article was submitted as a short version on December 13th 2017 and is under evaluation for publication at the 7th International Conference on Information Systems, Logistics and Supply Chain. It was also submitted as a complete version submitted to an academic journal. The research and redaction were made by me, Fanny-Ève Bordeleau, with support of my co-directors Elaine Mosconi and Luis Antonio de Santa-Eulalia. Proof of submission can be found in the appendices. Full reference: Bordeleau, F.-E., Mosconi, E., & Santa-Eulalia, L. A. (2018). Business intelligence value creation: A multiple case study in manufacturing SMEs. Submitted to the 7th International Conference on Information Systems, Logistics and Supply Chain, Lyon, France.


## 2. ABSTRACT

Industry 4.0 (I4.0) is affecting small and medium manufacturing enterprises (SMEs) just as much as big enterprises, yet they are underrepresented in literature. Models developed for large companies do not necessarily apply to SMEs. Furthermore, there are few studies focusing on the impact of business intelligence and analytics (BI&A) on value creation in I4.0, despite the importance of data and information in this context of digitalization of organizations. BI&A value creation from I4.0 transformation is an essential measure for companies wishing to improve their performance through new technologies. Using a multiple case-study design, this paper explores factors linked to BI&A business value creation in manufacturing SMEs that are undergoing an I4.0 transformation. Findings suggest company resources and capabilities are not sufficient to predict business value: organizational learning and organizational culture have a non-negligible influence for SMEs.

## 3. Introduction and research context

Industry 4.0 (I4.0) is often described as the introduction of cyber-physical systems into the manufacturing environment to facilitate industrial activities (Kagermann et al., 2013). Smart factories of I4.0 are notably characterized by the implementation of sensors and control systems in facilities, which generates a large volume of various industrial data at a great speed (Bagheri et al., 2015a). The approach to manage and analyze this volume, variety and velocity of data as well as its veracity and its value has been called big data (Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). Classical performance management systems (PMS) monitoring the past are not sufficient to assess business performance; performance monitoring must be continuous (Cocca & Alberti, 2010), which leads to more technological complexity when big data is involved (Biswas & Sen, 2016).

An approach traditionally employed to valorize data is Business Intelligence and Analytics (BI&A). It stands for an information systems approach helping companies make better business decisions and take better actions through the acquisition of data, analysis of information, and dissemination of knowledge (Eckerson, 2011). PMS have an important role in BI&A at the strategic level as they allow managers to have a balanced view of business performance (Cocca & Alberti, 2010; Eckerson, 2011), but with a focus on the past situation. In recent years, operational manufacturing BI&A has emerged as a way to valorize real-time production data by contributing to decision-making (Hänel & Felden, 2013). It offers an interesting albeit incomplete perspective from I4.0 data. I4.0 and the digital transformation represent innovative products, new services, changes in business models, improved competitiveness and improved process performance obtained through the use of emerging technologies (Schwab, 2016). To achieve these goals, manufacturing companies need to leverage both operational and strategic BI&A capabilities (Fink et al., 2017). General BI&A literature has covered business value creation in length from BI&A activities (Fink et al., 2017), but research has shown significant differences across different industry sectors (Elbashir et al., 2008) and, to the best of our knowledge, no single model describes the business value of manufacturing BI&A activities in SMEs. In fact, value creation coming from the usage of I4.0 data has been neglected by practitioners and scholars (Bordeleau, Mosconi, & Santa-Eulalia, 2018). Furthermore, both BI&A and PMS literature are lacking when it comes to considering the factors specific to small and medium enterprises (SMEs) (Bordeleau et al., 2018; Cocca & Alberti, 2010; Garengo & Bititci, 2007). Several resources, notably a competent and business-oriented technological staff, financial resources and robust technological infrastructure are more difficult to acquire and maintain for SMEs (Cocca & Alberti, 2010; Garengo et al., 2005).

Competitive advantage is derived from the judicious utilization of resources (Barney, 1991); companies with limited resources like SMEs could easily find themselves at a disadvantage. The availability of new data streams represents an interesting differentiating lever for companies (Kagermann et al., 2013) and especially for SMEs which need to be more flexible and more reactive to their environment (Cocca & Alberti, 2010). Thus, we are looking to determine the factors affecting business value creation from BI&A activities in manufacturing SMEs. This study contributes to academic knowledge by focusing on BI&A in manufacturing SMEs, an economically important but underrepresented class of enterprises in BI&A I4.0 literature (Bordeleau et al., 2018). It also serves managers by helping them understand their situation regarding BI&A and data valorization, and highlighting areas for improvement. In this context, we seek to answer the following question:

**RQ.** How do the factors relating to BI&A business value creation vary in manufacturing SMEs in the context of I4.0, compared to earlier BI&A literature?

To answer this question, we performed an empirical exploratory case study in manufacturing SMEs. This paper is organized as follows. Section 2 states the theoretical background on which the study is based and presents the research model.

Section 3 details the scientific methodology. Section 4 presents the results, Section 5 the analysis, discussion and Section 6 the conclusion.

# 4. THEORETICAL BACKGROUND

We covered literature on I4.0, information systems value creation, and BI&A, as well as value creation in I4.0. We present existing value creation models in information systems and BI&A literature and factors of value creation in SMEs. Then, a research model to assess business value from smart factories BI&A activities emerges. This model guided our empirical study.

## 4.1. BI&A and Industry 4.0

With objectives such as meeting customer requirements, optimized decision-making, creation of new value opportunities and being more agile in a fast-changing environment (Kagermann et al., 2013), I4.0 is a business-wide transformation rather than a collection of individual technological projects. Technological initiatives are driven by business objectives: the creation of a new service based on machine data, more efficient process through autonomous cyber-physical systems, or better operational decisions with increased production data quality and availability (Bordeleau et al., 2018). Many projects have in common the valorization of data into information usable to support human and machine decisions. In this context, I4.0 can benefit from BI&A, especially operational BI&A which exploits the large quantity of production data (Hänel & Felden, 2013). Yet, I4.0 literature has overlooked business objectives with only a small number of publications focused on supporting strategic management or supporting decision making, according to a recent systematic literature review in the area (Liao, Deschamps, Loures, & Ramos, 2017).

## 4.2. Business resources and capabilities in BI&A systems

The resource-based view of the firm (RBV) has often been used to describe the mechanism of information systems and BI&A business performance and value creation (Bharadwaj, 2000; Elbashir et al., 2008; Fink et al., 2017; Melville, Kraemer, & Gurbaxani, 2004; Ross et al., 1996). A company derives competitive advantage from rare, inimitable, immobile and heterogeneously distributed resources (Barney, 1991). For information systems, the main resources are the technical team, the technological infrastructure, and a strong relationship between senior management and the information technology department (IT) (Ravichandran, Lertwongsatien, & Lertwongsatien, 2005; Ross et al., 1996). Relationship between IT and management has been described in different ways in the literature, including partnership quality (Ravichandran et al., 2005). Research on critical success factors has used the term "alignment" (Eckerson, 2011; Yeoh & Koronios, 2010). Alignment implies that senior management and the IT team must agree on the role of the IT team. Furthermore, the IT strategy and the organizational strategy must be mutually coherent (Yeoh & Koronios, 2010).

RBV does not account for the way resources are applied and assumes a perfect utilization (Melville et al., 2004). It is a known limitation of the model which is often countered with the inclusion of contingency factors (Fink et al., 2017). Contingency theory is built on the rejection of a unique best way to achieve organizational goals; an organization must adapt its strategy to contextual factors (Taylor & Taylor, 2014). Performance is achieved by maintaining a fit between strategy and organizational context (Taylor & Taylor, 2014). In information systems, having the right resources is not sufficient, since resources are easily imitable (infrastructure) and mobile (human) (Bharadwaj, 2000). For resources to really lead to business value, a firm has to appropriately exploit these resources (Ross et al., 1996). Capabilities can be defined as "an organization's ability to assemble, integrate, and deploy valued resources, usually in combination or 'copresence'" (Bharadwaj, 2000, p.171). Furthermore, business value is not limited to competitive advantage, and the resources and capabilities model can also explain operational process level value often expressed as operational efficiency and effectiveness (Melville et al., 2004).

The distinction between operations and strategy is crucial for BI&A systems where there is a large difference between applications and users at different levels (Fink et al., 2017). BI&A systems are used on different organizational levels and for different purposes, from operators monitoring the performance of a process to a CEO consulting a performance dashboard or an analyst digging through data to discover actionable insights (Eckerson, 2011; Fink et al., 2017). There is a positive and significant link between operational process performance and organizational strategic performance (Elbashir et al., 2008) and this link is stronger in manufacturing companies (Elbashir et al., 2008). The same logic also led to the distinction between operational capabilities and strategic capabilities (Fink et al., 2017), since good capabilities at the operational level are not necessarily related to good capabilities across the organization (Fink et al., 2017).

### 4.3. The influence of organizational learning in SMEs

The utilization of resources to generate capabilities is heterogeneous in firms depending on organizational practices in place and especially organizational learning (Fink et al., 2017). March's (1991) organizational learning framework suggests two learning categories: exploration of uncertain and future possibilities and exploitation of certain and close possibilities. Companies relying excessively on exploitation limit their capacity to differentiate themselves while companies relying dominantly on exploration risk gaining more but also losing more (March, 1991; Ojha, Acharya, & Cooper, 2018). Organizations balancing exploitation and exploration activities, dubbed ambidextrous firms, are more likely to generate financial success (He & Wong, 2004). Organizational learning ambidexterity is hard to achieve, but gives the organization an inimitable advantage (Jansen, Tempelaar, van den Bosch, & Volberda, 2009) which in turns gives the company a competitive edge according to the RBV (Barney, 1991). Ambidexterity is facilitated by senior management's involvement in internal social connections (Jansen, Bosch, & Volberda, 2006) and collaboration (Jansen et al., 2009). It is also influenced by transformational leadership attitude, notably the articulation of a vision and high performance goals, being a model for employees, and fostering acceptance of the goals and the vision (Ojha et al., 2018). Senior management in SMEs is often more involved in day-to-day activities (Garengo et al., 2005) and their perception of performance influences decisions at all the levels of the organization (Raymond et al., 2013). Furthermore, SMEs are more likely than bigger firms to rely on feelings or subjective measures when deciding if a past behavior was appropriate, especially when the owner closely manages the business (Cocca & Alberti, 2010; Garengo & Bititci, 2007). Thus, organizational learning can potentially have a significant impact on the relation between resources and capabilities (Fink et al., 2017).

### 4.4. BI&A business value in SMEs

Since the introduction of the Balanced Scorecard (Kaplan & Norton, 1996), literature has agreed on the importance of not purely financially-oriented approach to organizational performance management (Cocca & Alberti, 2010; Eckerson, 2011; Fink et al., 2017). In SMEs, a PMS must also suit the owner’s conception of performance (Raymond et al., 2013). Yet, there is no consensus on the measurement of processes and operational value from BI&A activities. Hänel and Felden (2013) suggest value comes not only from financial benefits, but must also be evaluated from the customer’s point of view. Melville et al. (2004) define business process performance as “Operational efficiency of specific business processes, measures of which include customer service, flexibility, information sharing, and inventory management” (p. 295). They suggest measures of performance must be tailored to the process studied. Elbashir et al. (2008) build on this definition and add operation effectiveness to include effects on other processes in the supply chain. Furthermore, rather than adapting their questionnaire items to a specific process, they divide process performance into supplier and partner relations, process efficiency, and customer intelligence benefits. Ravichandran et al. (2005) suggest profitability, productivity and financial performance compared to the competitors in the last three years. Finally, Fink et al. (2017) defines operational value as process efficiency improvements, including cost reductions and increased productivity.

All of the above used perception-based measurements since subjective measures are easier to obtain, the objective values might be confidential, and some benefits are qualitative or intangible (Elbashir et al., 2008). Furthermore, in SMEs the managers are closer to the operations and have a good situation awareness, allowing them to evaluate their quality and on-time delivery performance, for example, even if they do not formally compile the indicator (Hvolby & Thorstenson, 2001). However, a mix of objective and subjective measures offers a more balanced result (Lönnqvist & Pirttimäki, 2006). A compromise between confidentiality and subjective evaluation are performance indicators variation, as used by Ravichandran et al. (2005) to confirm the perception-based items in their survey. Performance indicators may vary across industries but some are widespread in manufacturing companies. Bordeleau et al. (2018) review of I4.0 BI&A literature revealed nine performance indicators often cited to measure the success of a BI&A project. They are presented in Table 6.

Table 6. Manufacturing performance indicators, adapted from Bordeleau et al. (2018)

| | |
|---|---|
| 1 | Quality rate |
| 2 | Cost reductions |
| 3 | Efficiency rate |
| 4 | Up-time rate |
| 5 | Yield |
| 6 | Time to market |
| 7 | Overall equipment effectiveness (OEE) |
| 8 | Productivity |
| 9 | Energy consumption |

These indicators are not specific to I4.0. However, I4.0 has changed the way indicators are measured and presented: autonomous cyber-physical systems can self-adjust and indicators are calculated automatically, reducing even more process inefficiency (J. Lee et al., 2015). Manufacturing Execution Systems (MES) support real-time indicators (Dai et al., 2012) as opposed to data warehouse-based BI&A (Biswas & Sen, 2016). Indicators are easier to compile, more precise without human intervention and more financially accessible (Bordeleau et al., 2018). Performance indicators are thus less resources intensive, and can be presented in a graphical and visually appealing way, two essential conditions for SMEs (Cocca & Alberti, 2010).

## 5. A RESEARCH MODEL OF BI&A VALUE CREATION IN MANUFACTURING SME

We adopt the RBV to define a model of business value creation from BI&A activities in manufacturing SME. This model is presented in Figure 7. Following the literature, we describe the relevant resources for BI&A activities as the BI&A technical infrastructure, BI&A supporting team, and alignment between senior management and IT (Fink et al., 2017; Melville et al., 2004; Ravichandran et al., 2005; Ross et al., 1996). Alignment between senior management and IT also includes senior management involvement in the technological initiatives coordination in addition to the strategical alignment (Ross et al., 1996). BI&A technical infrastructure is defined as all the technologies available to the company and used for one or more of the following BI&A activities: acquisition of data, analysis of information and dissemination of knowledge (Eckerson, 2011). BI&A team is defined as the staff involved in one or more of the aforementioned BI&A activities.

Capabilities are described as the ability to exploit resources in company activities (Bharadwaj, 2000; Elbashir et al., 2008; Melville et al., 2004). Recently, Fink et al. (2017) suggested differentiating between operational and strategic capabilities. They define operational capabilities as exploitation of resources in process activities and strategic capabilities as exploitation of resources at the strategic management level. Therefore, having the resources in the first place is a necessary condition for capabilities.

**Proposition 1a and 1b.** Alignment between senior management and IT is a necessary condition for (a) operational BI&A capabilities and (b) strategic BI&A capabilities in manufacturing SME.

**Proposition 2a and 2b.** A competent and business-aware BI&A team is a necessary condition for (a) operational BI&A capabilities and (b) strategic BI&A capabilities in manufacturing SME.

**Proposition 3a and 3b.** A performant and available BI&A technical infrastructure is a necessary condition for (a) operation BI&A capabilities and (b) strategic BI&A capabilities in manufacturing SME.

[redacted]

Figure 7. BI&A value creation in manufacturing SME, adapted from Fink et al. (2017)

Several dimensions have been included in the measurement of IT effect on firm performance at an organizational, or strategic, level. Financial impacts (Bharadwaj, 2000), competitive impacts (Ross et al., 1996), market performance (Ravichandran et al., 2005) have all been studied. We adopt the most recent definition for BI&A strategic business value, which includes all of the above in addition to the ability to meet strategic objectives (Fink et al., 2017).

BI&A operational business value can be summarized as processes level efficiency and effectiveness (Fink et al., 2017). However, the measurement of efficiency and effectiveness is complex as discussed in Section 2.3. For this study, we interpret BI&A operational value as a mix from subjective efficiency assessment by a senior manager and performance indicator variation (Lönnqvist & Pirttimäki, 2006). BI&A operational capabilities have been proven to have a significant impact on firm strategic business value (Elbashir et al., 2008; Fink et al., 2017; Ravichandran et al., 2005), and operational capabilities were demonstrated to have a significant impact on BI&A operational business value (Fink et al., 2017).

**Proposition 4a and 4b.** Having good operational BI&A capabilities is a necessary condition for (a) operational and (b) strategic business value in manufacturing SME.

BI&A strategic capabilities have been shown to have a significant impact on strategic value creation but not on operational value creation, because senior managers' BI&A strategic capabilities have little impact on everyday operational value creation (Fink et al., 2017).

**Proposition 5.** Having good strategic BI&A capabilities is a necessary condition for strategic business value in manufacturing SME.

Literature shows BI&A strategic value is partially explained by BI&A operational value (Elbashir et al., 2008; Melville et al., 2004). This link is especially strong for non-service industry such as manufacturing (Elbashir et al., 2008), where operations including product manufacturing are essential to the business.

**Proposition 6.** Generating operational value through BI&A is a necessary condition for strategic business value in manufacturing SME.

The capacity to turn resources utilization into capabilities is influenced by organizational learning behavior (Fink et al., 2017). Exploitation is the organizational learning behavior relating to known certainties (March, 1991), and exploration is related to new and uncertain possibilities (March, 1991). These two behaviors are not mutually exclusive (Jansen et al., 2006; Ojha et al., 2018) and companies mastering both exploitation and exploration are less likely to be dependent on strong resources to generate strong capabilities (He & Wong, 2004). This concept has been named ambidexterity (Ojha et al., 2018).

**Proposition 7.** The link between resources and capabilities is moderated by a high organizational learning ambidexterity.

## 6. Research methodology

We study multiple cases to explore factors linked to business value generation from BI&A activities in manufacturing SMEs. Multiple case studies allow for a more complete and comprehensive view of the context than single case analysis (Yin, 2009), thus it is more appropriate to understand the relations between factors of BI&A business value creation, and to explore factors specific to manufacturing SMEs.

A case study protocol was developed following best practices (Yin, 2009) to ensure the research design was complete and feasible. The protocol helps to make sure the same methodology is applied for all the cases, ensuring a better reliability (Gibbert, Ruigrok, & Wicki, 2008). The steps are described in Table 7. The full protocol for this study is available on request excluding the identification of participants. Because the study addresses potentially strategic elements for the SMEs, their identity will not be disclosed. This research was approved by the research ethics committee of our institution prior to data collection. The case unit is defined as a SME since it started to employ BI&A activities including production data from cyber-physical systems or other I4.0 concepts.

Table 7. Content of a case study protocol, adapted from Yin (2009)

| **Case study protocol steps** |
|---|
| A. Introduction to the case study |
| 1. Research question and propositions |
| 2. Theoretical framework |
| 3. Role of protocol |
| B. Data collection procedures |
| 1. Identification of sites to be visited |
| 2. Data collection plan |
| 3. Expected preparation prior to visit |
| C. Outline of case study report |
| D. Case study questions |
| E. Data analysis plan |

The cases were chosen based on several criteria, forming the boundaries of generalization (Yin, 2009). The companies are in the manufacturing sector. They are either actively pursuing an I4.0 digital transformation or have manifested an interest in doing so in the near future. They represent different industry domains and business models and they are in different geographical regions and urban density area. Replication logic dictates the results should be comparable regardless of these control variables. Finally, we made sure all the enterprises were considered SMEs as per the OECD recommendation of 250 or fewer employees (*OECD SME and Entrepreneurship Outlook 2005*, 2005). The number of cases was not decided before the study: we defined a stop criterion when results covered a large range of answers to the capabilities and business value creation variables and when new cases did not provide new information. The final number of cases is six cases, sufficient to detect major logical flaws in the model and as a basis for analytical generalization (Gibbert et al., 2008). The case studies were executed between August and September 2017.

The interviews were split into two parts. The first round involved an open-ended discussion on their environment, internal practices, evaluation of the digital transformation, and performance measurement. In three cases, several managers were involved in this discussion. In the other cases, for availability reasons, only one senior manager was interviewed. This interview had an exploratory goal and was used to better understand their context.

A second interview followed with a single manager for each SME. This interview followed a semi-structured questionnaire. We asked a consultant specialized in coaching of manufacturing SMEs to revise the questionnaire prior to the interviews. Only minor wording modifications were made at this step. To gain a better understanding of the enterprise context, the question was asked as a statement, then the manager was invited to elaborate on whether they agreed on the statement and finally they were invited to choose, from a scale of 5 anchored between very strong and absent or very weak, the position that better represented their company.

The items were adapted from existing literature to ensure better construct validity (Gibbert et al., 2008). Operational BI&A capabilities, strategic BI&A capabilities, and BI&A strategic business value were adapted from (Fink et al., 2017). BI&A operational business value items were adapted from (Fink et al., 2017) and from (Elbashir et al., 2008), while senior management and IT alignment, BI&A team and BI&A technical infrastructure were adapted from (Fink et al., 2017) and (Ross et al., 1996). Organizational learning items were adapted from (Jansen et al., 2006) and (Fink et al., 2017). Items were translated into French and interviews were conducted in French. The complete questionnaire is available on request. Interviewees were invited to comment on the first version before publication, to ensure their statements were correctly reported.

Qualitative and quantitative data was analyzed based on the research propositions on a cross-case analysis. Because of the small sample size, patterns were manually coded for each proposition and dimensions. We used keywords mentioned by interviewees to group subjects and objects. We enriched this interpretation with the available qualitative data. Having a clear research framework and comparing results to previous literature ensures good internal validity (Gibbert et al., 2008).

# 7. RESULTS

## 7.1. Cases description

The characteristics of the SMEs studied in this paper are presented in Table 8, from the smallest organization to the largest. The cases were selected to cover literal replications as well as theoretical replication within the case boundaries (Yin, 2009), notably concerning industrial sectors, size, types of ownership, BI&A activities, and next major technological initiatives. The definition of SME varies greatly between countries. In this paper, we adopt the general guidelines of OECD which considers companies of fewer than 10 employees as micro SMEs, companies of under 50 employees small companies, and companies of more than 50 but fewer than 250 employees as medium-sized companies (*OECD SME and Entrepreneurship Outlook 2005*, 2005).

Table 8. Description of cases

| | **Industrial sector** | **Size** | **Sales** | **Ownership** |
|---|---|---|---|---|
| **SME1** | Industrial equipment | Micro | <2M$ | Single founder manager |
| **SME2** | Die manufacturing | Small | 2M$ to 19M$ | Four founder managers |
| **SME3** | Telecommunications | Medium | 2M$ to 19M$ | Non-manager shareholders |
| **SME4** | Electronic components | Medium | 2M$ to 19M$ | Three non-manager founders |
| **SME5** | Wood furniture | Medium | 20M$ to 50M$ | Shared by founder manager and shareholder company |
| **SME6** | Lumber | Medium | >50M$ | Investment company shareholder |

There is a great diversity in the types of BI&A activities in the interviewed cases. SME1 relies on financial lag indicators to monitor business performance. They wish to implement a relational database to introduce ad hoc requests. They currently do not employ any IT resources and have no plan to hire in the foreseeable future. Technologies to them are tools to facilitate day-to-day activities.

SME2 struggles with basic PMS, and their data is not digitalized consistently. They wish to implement an ERP. Their IT internal resources are mostly focused on the engineering and production systems, with little support for decisional applications. They acknowledge the potential strategic impacts of information systems, but they have yet to integrate information system strategy in their business strategy.

SME3 relies on transactional systems with built-in reports and indicators. Any other activity, such as updating of company scorecard, must be performed manually by managers. They also lack centralized data. They are evaluating their needs to upgrade their ERP and enterprise database. Their IT staff is mostly focused on the production and engineering systems with little to no support for managers in their BI&A activities. Despite this, they have recently taken the time to evaluate the impact of information systems and new technologies on their business model. At the time of the interviews, they were engaged in a strategic planning exercise and the digital transformation was an important subject.

SME4 has decentralized BI&A activities based on a centralized database. Senior management has selected enterprise-wide Key Performance Indicators (KPIs) in their balanced scorecard and revise them annually. BI&A levels vary between departments, the most advanced being sales, with a predictive analysis model in use. They are supported by a small internal IT team, but no dedicated BI&A internal resources. They have integrated I4.0 challenges in their organizational strategy and have a digital roadmap.

SME5 has a dedicated BI&A team, including an analytics specialist. Managers have access to an enterprise BI&A system with controlled reports and indicators. Ad-hoc analysis is also available, although the BI&A team is too busy to be able to serve all requests. Their current projects are in line with the recent technological advances: taking advantage of cyber-physical systems for raw material management and nesting, and participation of the client in the manufacturing process. They update their I4.0 roadmap on a regular basis with visits to suppliers or showcase plants. Digitalization is a central element of their organizational strategy.

SME6 has a real-time monitoring of production processes, including advanced autonomous systems for the cut of wood logs and quality monitoring. Some of the senior managers have access to a self-service BI&A platform, but BI&A effectiveness is limited by the lack of a central infrastructure. Furthermore, they have no IT team and no dedicated information chief officer. They are working on an enterprise data infrastructure. However, their digital projects are evaluated individually, without a proper roadmap or strategy to guide them.

### 7.2. Cross-case analysis

The results for the second part of the interview with the closed questions are presented in Table 9.

Table 9. Results of second part of interviews

| | **SME1** | **SME2** | **SME3** | **SME4** | **SME5** | **SME6** |
|---|---|---|---|---|---|---|
| Senior management and IT alignment [SM] | Strong (4) | Neutral (3) | Neutral (3) | Strong (4) | Neutral (3) | Neutral (3) |
| BI&A team [BT] | Neutral (3) | Neutral (3) | Weak (2) | Strong (4) | Neutral (3) | Strong (4) |
| BI&A technical infrastructure [IN] | Very strong (5) | Weak (2) | Neutral (3) | Strong (4) | Strong (4) | Weak (2) |
| Exploration | Neutral (3) | Weak (2) | Strong (4) | Weak (2) | Very strong (5) | Strong (4) |
| Exploitation | Very strong (5) | Strong (4) | Strong (4) | Strong (4) | Very strong (5) | Strong (4) |
| Organizational learning ambidexterity | Absent/ very weak (1) | Absent/ very weak (1) | Strong (4) | Absent/ very weak (1) | Very strong (5) | Strong (4) |
| Operational BI&A capabilities [OC] | Neutral (3) | Absent/ very weak (1) | Weak (2) | Strong (4) | Strong (4) | Strong (4) |
| Strategic BI&A capabilities [SC] | Absent/ very weak (1) | Neutral (3) | Neutral (3) | Strong (4) | Very strong (5) | Neutral (3) |
| BI&A operational business value [OV] | Neutral (3) | Weak (2) | Neutral (3) | Neutral (3) | Strong (4) | Strong (4) |
| BI&A strategic business value [SV] | Neutral (3) | Neutral (3) | Neutral (3) | Neutral (3) | Very strong (5) | Strong (4) |

| Legend: | Very strong (5) | Strong (4) | Neutral (3) | Weak (2) | Absent/ very weak (1) |
|---|---|---|---|---|---|

The analysis is made for each proposition individually. The propositions state that a higher level of the independent variable than the level of the dependent variable is a necessary condition. We do not test for sufficient conditions in this study. Hence, a proposition for which the levels of the independent variable is higher than the level of the dependent variable is validated for the sample, while a high level of the dependent variable without a corresponding high level of the independent variable would suggest the rejection of the proposition.

**Alignment between senior management and IT [SM]**

Results for this section highlight the differences of SMEs. Senior managers are not only involved in the choice of technological objectives and IT strategy: they realize the projects. An example is SME3, where the CEO supervises the ERP integrator. Few technological standards have been established by the managers. They tend to evaluate their needs before every project, but are still careful about data consistency. The manager from SME6 notes he would not approve a new technology that is not compatible with their accounting system. This results in a generally neutral to strong SM, as shown in Table 9. SME3 manager illustrates with the example of their current ERP. Because they cannot get sales data on the same system, they seek to switch to an ERP more adapted to their needs, but they are not committed to a single supplier. Making sure the internal IT team agrees with the business strategy is trickier for larger companies. When asked if she thought the IT manager understood the business priorities, the manager from SME5 said:

> Usually yes, but sometimes there are disagreements, or unaligned visions. This is the case right now with one of our projects, where the president and the IT manager don’t agree on a technological choice.

The manager notes disagreements are usually due to a lack of understanding, with the senior management failing to understand the technological complexity, and the IT manager not understanding the customers’ points of view.

**BI&A team [BT]**

We first listed every BI&A activity performed by the organizations, as presented earlier. For each BI&A activity, we discussed who oversees data manipulation, analysis, and diffusion (e.g. the BI&A team) and who used the information (e.g. data users). For most companies, senior managers tended to be both data users and perform activities expected of a BI&A team in larger companies, such as data collection and integration. For most interviewed managers, the technical skills of their BI&A team were perceived as adequate, despite having to do a lot themselves. Most also agreed their team were keeping their technical skills up-to-date, although some do not take the time to document their learning activities. All interviewed managers, except SME3 where projects are led and realized by senior managers, declared wishing their team was more business aware. The manager from SME5 declares:

> It's hard to understand data context, its source, how it's collected, how human mistakes can affect its quality… I don't know if it's a matter of lacking skills, sometimes it's more about not having a 360-degree view of the business context.

The manager from SME1 mentions:

> They are focused on their task. Sometimes they'll see opportunities for improvement, but that is still usually technical improvement, not really for example, costs improvements since they don't know production costs.

This distinction is important in order to understand these companies: their staff is technically competent, but they do not take business related initiatives and they often do not consider the business impacts of their actions. Technical support was often more operationally oriented. Several managers wished they were more supported in their data analysis, as pointed out by SME3:

> When a production system needs debugging, they [the IT team] are available, but when I need help with Excel, I have to find the solution myself.

Technological data-related projects leadership varied greatly. SME5 and SME4 prefer entrusting leadership of the projects to the employees who will benefit from it, while the others cannot spare the human resources and rely on the senior managers. In all companies, the IT team mostly had a supporting role in technological projects. Overall, managers generally could not say their BI&A team was a strong resource in their company, but as shown in Table 9, the larger SMEs interviewed have a slightly better BI&A team and they also have a formal head of IT or head of BI&A, in contrast with the smaller companies.

**BI&A technical infrastructure [IN]**

Table 9 highlights the lack of uniformity across the cases. We asked the managers to answer the question while thinking of all the technologies of the company dedicated to valorizing data, including database, decision support systems, reports, and self-service tools. Three companies declared having a performant BI&A infrastructure. SME5 and SME4 can rely on a centralized, enterprise-wide database to access data from most of the different business processes. They both wish the few systems not included, like the accounting systems, were available through this platform. SME4 illustrates:

> There are few systems left where the data was not centralized, and some machines are not linked, but we are working on it; it’s going to be a big step when everything is done.

SME1 owner-manager’s evaluation of the infrastructure might be surprising at first, since no transactional nor decisional system is implemented yet in the company. However, for this manager, performance is defined essentially by the financial success of the company. Since the technology available allows decision-makers to monitor financial indicators adequately, the manager is satisfied.

Managers from SME6, SME2, and SME3 identify the lack of communication between their different systems, such as accounting, purchasing, production, and maintenance systems, as the principal culprit for the lack of performance of their BI&A infrastructure. SME6 and SME3 are engaged in large-scale projects to allow data to flow digitally, and eventually automatically. SME6 comments:

> I have [this self-service app] installed, but I only use it for financial performance since production and procurement data is not linked into it. I have to get everything into Excel if I want a complete view.

SME2 has no infrastructure at all. They admit to wasting a lot of time and making too many errors when manually or orally processing information.

**Operational BI&A capabilities [OC]**

All interviewees understood the potential for performance gains through the I4.0 technologies and all agreed on the importance of valorizing available data, even though some of them were not doing many BI&A activities. However, only SME4 and SME5 have integrated the digital transformation explicitly in their strategy. They have the highest capabilities, both operational and strategic. Table 9 shows that there is a correlation between company size and higher operational capabilities. Real-time and integrated analysis are especially difficult for the smaller SME1, SME2, and SME3. SME3 manager notes:

> People are careful to base their decisions on data, and senior management encourages this behavior, but not all systems have available KPIs. We don't have enterprise-wide real-time analysis and for continuous improvement initiatives, data is not systematically used to model the results but it is used to identify the zones of improvements.

SME4, SME5, and SME6 note important differences between the different enterprise functions. They are confident on past work and are still working to implement BI&A where needed. SME4 manager notes:

> We still have a lot to do, but what's been done, it's well done, it's used, it's appreciated, and it's here to stay.

SME5 identified a lack of unified control on data and a lack of resources as limits to BI&A capabilities.

> It's open wide. I can start with the same data as someone else, but because I'm not using the same definition, we won't get the same numbers. Also, IT doesn't deliver, they just have too much of a backlog.

### Strategic BI&A capabilities [SC]

Strategic BI&A capabilities were in general better than operational capabilities, as illustrated in Table 9. An exception is SME6, who cites lack of access to external and market data, and difficulty of putting together the internal data drawn from the different systems.

> It's hard, and it's time-consuming. I need to get everything into Excel, manipulate it, and I still don't have access to important data.

SME5 notes the difficulty of getting a complete view of the company's situation.

> It's just too much data. There is always cleanup to do.

SME3 also wishes there were more market data available.

> We could do more, we are doing tradeshows; we could do more to bring data home. We've also been offered to buy external data, but we don't know if it's worth the price.

SME1 owner-manager knows he would need data on costs and manpower to be able to monitor the business performance. He notes:

> We don't really know what we should improve; we don't even know what's possible, what solutions exist. […] We don't always manage to find the problem.

They also wish market data was more precise: their accountant compares them to companies outside of their sector.

### BI&A operational business value [OV]

The items of this section are based on common performance indicators, yet several companies answered on a subjective perception-based basis, since their company did not monitor the chosen indicators. These results are coherent with previous research (Hvolby & Thorstenson, 2001). SME5 and SME3 suggested asking more questions on processes other than production of goods, such as sales closing rate. SME5 illustrates:

> Knowing we produced quality goods is fine, but what's really important for the client is how quick we can process his order, and for us the biggest delay is the administrative passing time.

While production is a vital function for manufacturers, so are the sales, administrative transit time, service return rates, on time delivery, etc. Perception-based items are still reliable and widely used in BI&A literature (Elbashir et al., 2008; Fink et al., 2017), and data for this dimension is relevant, but in a future study the measurement of BI&A operational business value could be improved. When asked whether performance indicators were sufficient as the sole measure of performance, all managers, except SME4, insisted that qualitative data on the internal environment (like employees' engagement, work climate and perception of tendencies) were equally important as quantitative data. SME4 manager claimed that if performance indicators are chosen to represent all perspective of a business, they should be a good measure of performance. He notes:

> We revise which indicators are our KPIs every year, or more often if there are any big changes. If they're chosen with care, they represent every important measure to monitor, including customer satisfaction or intangible values.

The most popular performance indicators were: quality rate, productivity (sales revenues per worked hours), employee occupation rate, capacity level, service calls, on-time delivery, returns rate and client satisfaction. The two larger companies in the sample have the best operational business value, as shown in Table 9.

**BI&A strategic business value [SV]**

The interviewees were more confident in answering strategic business value questions, stating that they are better informed on firm performance than on specific process indicators. They have the available quantitative (revenues, profits) and qualitative (better understanding of clients, better decisions) information on their company. A notable exception is information on market shares, which relied on perceptions. As for operational business value, the larger firms have more strategic business value from BI&A, as illustrated in Table 9. All interviewed managers insisted on the essential role of technologies and information for the future of their company. For SME5, future growth depends on the successful integration of technologies:

> If we want to sustain our growth, we need [the new technologies]. It's also a matter of culture and habits, senior management has been traveling, seeing other more advanced plants; we've been dreaming about the new plant for years.

**Organizational learning ambidexterity [ER and ET]**

Exploration and exploitation were evaluated separately, then ambidexterity was evaluated. Three companies are much more exploitative than they are explorative: SME1, SME2 and SME4, as shown in Table 9.

SME2 and SME4 have settled on a growth rate they feel comfortable with and do not hesitate to refuse a contract. The ability to satisfy existing clients is more important to them than getting new clients. In both companies, this choice was made because they have limited resources. SME2 manager notes:

> If I want to get a higher turnover, I'd have to hire another machinist, another designer. They aren't exactly common in the employment market right now.

SME1 manager's position is more nuanced. They are looking for new clients and new markets but they are not experimenting, taking great risks, or looking for variation. Exploitative behavior was much more representative of their business: refinement, efficiency, execution.

SME3 and SME6 have a strong rather than very strong position on both exploitation and exploration. They cite resource allocation as the principal limit, especially for innovative activities. SME5 was the only company with strong levels of both exploration and exploitation. Flexibility and high quality for the customer are two of their central values, possibly explaining their ambidextrous focus.

## 8. Discussion

The goal of this study is to explore factors related to BI&A business value creation for manufacturing SMEs, around several propositions listed in Section 2.5.

**Proposition 1a.** Alignment between senior management and IT [SM] for operational BI&A capabilities [OC]

Table 10. SM link with OC

| | SME1 | SME2 | SME3 | SME4 | SME5 | SME6 |
|---|---|---|---|---|---|---|
| SM | | | | | | |
| OC | | | | | | |

| Legend: | Very strong (5) | Strong (4) | Neutral (3) | Weak (2) | Absent/ very weak (1) |
|---|---|---|---|---|---|
| | | | | | |

SM is often cited as an essential success factor for BI&A systems (Yeoh & Koronios, 2010), yet for SME5 and SME6, SM is weaker than OC as illustrated in Table 10. The manager for SME5 mentioned the lack of alignment comes from the diverging views of the owner-manager and the chief information officer. There is therefore a conflict, but the owner-manager, being a strong-minded and visionary individual, usually imposes his view in the end. SME6 BI&A activities are siloed. There is no company-wide BI&A standard nor strategy. However, individually the technically savvy departmental heads make good use of data in their operations. In both cases, personal characteristics of the managers appear more important than alignment of IT. Overall, we have not identified a strong link between SM and OC, although there seems to be a weak link since the proposition stands for four of the cases. The presence of a significant link is supported by existing theory (Fink et al., 2017; Ross et al., 1996).

**Proposition 1b.** Alignment between senior management and IT [SM] for strategic BI&A capabilities [SC]

Table 11. SM link with SC

| | SME 1 | SME 2 | SME 3 | SME 4 | SME 5 | SME 6 |
|---|---|---|---|---|---|---|
| SM | 9 | | | | | |
| SC | | | | | | |

Proposition 1b is true for all cases except SME5, as highlighted in Table 11, for the reasons mentioned above. The impact on strategic capabilities in SME5 could be mitigated by strong leadership style (Garengo & Bititci, 2007). Since the relationship is true for all five other organizations, we conclude there is a strong link between SM and SC, in accordance with theory (Fink et al., 2017).

**Proposition 2a.** BI&A team [BT] for operational BI&A capabilities [OC]

Table 12. BT link with OC

| | SME 1 | SME 2 | SME 3 | SME 4 | SME 5 | SME 6 |
|---|---|---|---|---|---|---|
| BT | | | | | | |
| OC | | | | | | |

Table 12 shows proposition 2a is true for all except SME5. Of all the interviewed cases, SME5 is the most advanced in its BI&A activities. The managers have had access to an enterprise database with reports and self-service data for many years. KPIs were selected for all hierarchical levels based on a balanced and centralized reflection. The IT team has developed analytics capabilities. Yet, the IT manager declares having too much to do and not being able to serve all requests. This perception was confirmed by another senior manager, who stated being overwhelmed by the large quantity of data, yet having the feeling she never has quite the right data. SME5 BI&A

might be entering a maturity stage of growing BI&A activities and uncertainties (Eckerson, 2011). During this stage, it is common to observe real or perceived regressions which could explain SME5 manager's low evaluation of BI&A team despite seemingly good capabilities. Since the proposition is true for all other companies, we conclude there is a strong link between BT and OC, as expected from theory (Fink et al., 2017).

**Proposition 2b.** BI&A team [BT] for strategic BI&A capabilities [SC]

Table 13. BT link with SC

| | SME 1 | SME 2 | SME 3 | SME 4 | SME 5 | SME 6 |
|---|---|---|---|---|---|---|
| BT | | | | | | |
| SC | | | | | | |

Proposition 2b is not true for SME3 and SME5, as shown in Table 13. SME3 BI&A team is not business aware, but since they do not offer support to the managers, their competency does not affect strategic BI&A capabilities. A manager mentioned having to look up his answer on the web when he needs to change something in his reports. The interviewee of SME5 was very critical of their internal BI&A team. She felt they were falling short of the expectations of the C-suite especially concerning business comprehension. These findings are similar to the conclusions of previous research (Fink et al., 2017), but nevertheless this should be further investigated. The situation in SME5 was discussed in proposition 2a: the perception is possibly biased because of the current work load of the BI&A team and might be temporary. Since two of the cases disprove the proposition, our evidence suggests the link between BT and SC is weak rather than strong.

**Proposition 3a.** BI&A technical infrastructure [IN] for operational BI&A capabilities [OC]

Table 14. IN link with OC

| | SME 1 | SME 2 | SME 3 | SME 4 | SME 5 | SME 6 |
|---|---|---|---|---|---|---|
| IN | | | | | | |
| OC | | | | | | |

Proposition 3a is not true for SME6, as made evident in Table 14. Despite a weakly perceived infrastructure performance, SME6 has good operational BI&A capabilities. In SME6, the administrative managers do not have access to a centralized decision support system but the manufacturing operations have real time monitoring and analysis imbedded on the manufacturing equipment. Thus, operations have high capabilities, but management perceives the overall infrastructure as non-performant. The model could be improved by integrated objective measurement of capabilities as suggested by the best practices in the measurement of BI&A (Lönnqvist & Pirttimäki, 2006) to mitigate the impact of negative bias of the respondent. Despite SME6 we observed a strong link between IN and OC since the relationship is true for all five other companies. These findings are expected (Fink et al., 2017).

**Proposition 3b.** BI&A technical infrastructure [IN] for strategic BI&A capabilities [SC]

Table 15. IN link with SC

| | SME 1 | SME 2 | SME 3 | SME 4 | SME 5 | SME 6 |
|---|---|---|---|---|---|---|
| IN | | | | | | |
| SC | | | | | | |

Proposition 3b is not true for SME2 and SME6, as shown in Table 15. SME2 has no BI&A technical infrastructure and SME6 manager must extract data in Excel from different systems to be able to use them. All other companies have access to at least basic reports and automatically compiled KPI. SME2 and SME6 managers have to "make do" with what they have, trading weak infrastructure for extra handwork. This behavior, while inefficient, is coherent with observed lack of resources in SME (Cocca & Alberti, 2010) and could indicate direct involvement and leadership of senior managers is an important factor in SME. We conclude there is a weak link between IN and SC.

**Proposition 4a.** Operational BI&A capabilities [OC] for operational business value [OV]

Table 16. OC link with OV

| | SME 1 | SME 2 | SME 3 | SME 4 | SME 5 | SME 6 |
|---|---|---|---|---|---|---|
| OC | | | | | | |
| OV | | | | | | |

Table 16 shows proposition 4a is true for all cases except SME2 and SME3. SME2 does not have operational BI&A capabilities; the measurement of the link between OC and OV for them is not relevant. OC for SME3 is lowered by a lack of real-time and modeling data activities, but they do have a data-driven culture and strong executive leadership. SME3 manager mentioned the sales team is performing despite weak resources thanks in part to this data-driven culture. It is possible that organizational culture and leadership have a larger impact on business value creation in smaller companies where a present and determined manager can lower the impact of weaker capabilities (Garengo & Bititci, 2007). Our data suggest a weak link between OC and OV, lower than expected based on previous literature (Fink et al., 2017).

**Proposition 4b.** Operational BI&A capabilities [OC] for strategic business value [SV]

Table 17. OC link with SV

| | **SME 1** | **SME 2** | **SME 3** | **SME 4** | **SME 5** | **SME 6** |
|---|---|---|---|---|---|---|
| OC | | | | | | |
| SV | | | | | | |

Proposition 4b is not true for SME2 and SME3, as shown in Table 17. It is probable the impact of the manager's leadership style is underestimated in the model. Managers from both organizations rely on intuition and are not achievement oriented. Their perception of the value of a business includes concepts such as employee satisfaction. Classical measurement items built for large organizations are less precise and less appropriate in their context (Garengo & Bititci, 2007). There seems to be a weak link between OC and SV, in contrast to previous research which demonstrated a strong and significant link (Fink et al., 2017), so this would need to be further investigated to evaluate if company size has a moderating effect on the link between operational BI&A capabilities and strategic business value creation.

**Proposition 5.** Strategic BI&A capabilities [SC] for strategic business value [SV]

Table 18. SC link with SV

| | **SME 1** | **SME 2** | **SME 3** | **SME 4** | **SME 5** | **SME 6** |
|---|---|---|---|---|---|---|
| SC | | | | | | |
| SV | | | | | | |

Proposition 5 is true for all the sampled cases except SME1 and SME6, as highlighted in Table 18. The BI&A strategic capabilities hardest to master for SME6 are the ones related to external information. It is a tendency across the cases, with four out of six companies mentioning not having access to reliable enough information on their competitors and the market. For SME6, an added difficulty is the external owners who are mostly interested in financial performance and limit the managers' capacity to orient the company as they wish. The role of the owner is not included in the theoretical model of this study, but it seems it could be an important moderator of the link between capabilities and business values for SME, coherent with literature on PMS in SMEs (Garengo & Bititci, 2007). The owner of SME1 mentioned not needing data to analyze the situation of his company except financial indicators, since to him, the success of a firm is defined by its finances only. Hence the SC questions related to the data analysis of the environment, the strategy and business model were not relevant to him. We conclude there is a weak link between SC and SV, which is not coherent with previous literature (Fink et al., 2017) who concluded there is a significant impact. However, it is interesting to note the two organizations for which proposition 5 is not true are the companies who do not have a balanced definition of performance. This is coherent with past studies on SMEs which showed these businesses were less likely to follow scientific advice concerning the definition of performance (Raymond et al., 2013).

**Proposition 6.** BI&A operational business value [OV] for BI&A strategic business value [SV]

Table 19. OV link with SV

| | SME 1 | SME 2 | SME 3 | SME 4 | SME 5 | SME 6 |
|---|---|---|---|---|---|---|
| OV | | | | | | |
| SV | | | | | | |

This proposition is true for all interviewed companies except SME2 and SME5, as evidenced in Table 19. SME2 does not use any operational performance indicator; their evaluation of OV was entirely based on intuition and perception. Furthermore, several indicators were less appropriate for this small company looking to maximize man hours instead of machine uptime. Thus, OV measurement for SME2 is not as precise as in the other cases and does not represent the owner's definition of performance. The same comment about not looking to maximize machine uptime was made by the managers of SME1, SME3 and SME4, but these companies follow the other indicators in the questionnaire and were able to evaluate their performance based on the other items. Furthermore, SME3 and SME5 express the need to evaluate sales operational performance to have a true portrait of operational performance. The slightly lower OV for SME5 compared to SV is due to inefficiencies in a bottleneck process, which leads to higher lead time. Fortunately for them, their lead time is still comparable to the competition and thus had no impact on the firm's performance. Overall, data suggest a weak link between OV and SV, whereas literature suggests a significant link (Fink et al., 2017). Further research is needed on a measurement item for BI&A operational business value for manufacturing SME.

**Proposition 7.** The link between resources and capabilities is moderated by organizational learning ambidexterity.

Table 20. Ambidexterous organizational learning effect

| | **SME 1** | **SME 2** | **SME 3** | **SME 4** | **SME 5** | **SME 6** |
|---|---|---|---|---|---|---|
| SM | | | | | | |
| BT | | | | | | |
| IN | | | | | | |
| AMB | | | | | | |
| OC | | | | | | |
| SC | | | | | | |

Table 20 highlights that ambidexterity could moderate the link between resources and capabilities. The three ambidextrous companies SME3, SME5 and SME6 all have on average lower scores on resources than on capabilities. This is especially strong for SME5, which expressed high level of both exploration and exploitation. For the other organizations, resources have an equal or higher level than capabilities. The effect of ambidexterity is enough to explain the weak links in P1a and P2b but not P3b. An impact was expected according to theory (Fink et al., 2017; He & Wong, 2004), but as not all resource propositions can be explained with P7, we conclude there is a weak link.

[redacted]

Figure 8. Revised model

The revised model is presented in Figure 8. The evidence gathered during this study highlights several differences with SMEs compared to larger companies. Most notably, these factors are insufficient to explain operational and strategic BI&A business value. For companies like SME1, SME2 and SME6, the measurement of business value does not fit their personal definition. For SMEs, a universal definition of business value is not appropriate. This finding was suggested by previous studies (Raymond et al., 2013) and a measurement method for business value in SMEs remains a research gap.

The addition of other resources could improve the model. There is a link between organizational learning ambidexterity and capabilities, but the strength of this link is still up for debate. Furthermore, this model does not account for the personality and leadership style of the managers, factors demonstrated to have links with ambidexterity (Ojha et al., 2018) and firm performance (Garengo & Bititci, 2007). Lastly, the implication of the managers was not considered. In the SMEs studied, the managers did manual operations related to their BI&A activities to compensate for the lack of human resources. This factor should be included in future studies, compared with larger companies with BI&A and IT teams.

## 9. CONCLUSION

SMEs will engage more in BI&A and data valorization activities in the future, with the increased availability of data and pressure from international competition. It is important to understand the factors specific to SMEs leading to value creation from BI&A activities.

This study can help managers of SMEs in the allocation of resources. BI&A team and infrastructure can facilitate better operational capabilities while a good alignment between senior management and IT is linked with better strategic capabilities. Furthermore, having ambidextrous organizational learning habits can mitigate the lack of resources and should thus be considered a business best practice. Other stakeholders such as financing organizations or governments can also benefit from this study, by considering factors linked to personality and organizational culture when evaluating manufacturing SMEs.

This study contributes to academic knowledge by highlighting differences between SMEs and larger enterprises related to BI&A value creation. It also paves the way to other exploratory studies to understand the impacts of the managers' behavior and leadership style on capabilities, or to studies focusing on the definition of performance and business value in SMEs. Confirmatory studies could also be made on a larger sample to gain empirical quantitative evidence of some of the conclusions.

There are limits to this study. The small number of cases and convenient sampling method do not permit a broad generalization, however, this exploratory study was aiming at a logical and contextual rather than statistical generalization (Yin, 2009). Furthermore, care was taken to select representative cases to identify potential logical flaws in the model. Qualitative data was crucial to understand the context and mitigate this impact.

Future studies need to test an improved model on a larger sample of manufacturing SME. Broader than organizational learning, organizational culture and leadership styles seem to be determinant factors for SMEs (Garengo & Bititci, 2007). These contingency factors should be included in a future research, in addition to managerial practices and external context.

# CONCLUSION

This master's thesis aimed at exploring the factors influencing value creation from BI&A activities in manufacturing companies. It consists of two articles, one literature review accepted at the 51$^{rst}$ Hawaii International Conference for System Sciences, and one multiple case-study submitted as a short version to the 7$^{th}$ International Conference on Information Systems, Logistics and Supply Chain and as a complete version submitted to an academic journal.

The literature review highlighted the current state of the art and some research opportunities in BI&A in manufacturing Industry 4.0 research. It showed research is currently focused on two types of BI&A activities: first, developing a technological architecture allowing for real-time production data processing, and second, developing analytics and data sciences application for manufacturing. Research on the subject is still in an early diverging state, and empirical studies are still rare. There are still plenty of opportunities to measure the impacts of the developed applications for the industry.

The multiple case-study demonstrated the difference in the factors influencing BI&A business value creation in SMEs compared to larger companies, in the manufacturing sectors. In SMEs, the strategic aspect of BI&A is often the sole responsibility of the senior management, with little to no IT or super user support. Furthermore, organizational culture contingency factors, such as organizational learning behavior, leadership style, and involvement of the owner, seem more prevalent in SMEs compared to previous studies focussed on large companies.

This thesis contributes to academic knowledge in several ways. The literature review gives a portrait of the state of the art on BI&A and Industry 4.0 and shows research opportunities. The case study highlights several factors differentiating SMEs from larger companies concerning BI&A business value creation. BI&A business value creation models can thus be improved to include the specificities of this important population of enterprises.

Managers and business analysts can gain a better understanding of the factors facilitating BI&A business value creation, and thus guide companies in creating favorable conditions. Notably, the results of this study highlight the link between organizational learning ambidexterity and high BI&A capabilities, even when the organizations have lower resources. Managers of manufacturing SMEs need to understand the role of organizational factors in their digital transformation; success is not exclusively determined by human and technological resources.

There are several limits to this study. The systematic literature review included only English publications, which means some important work might have been forgotten. The empirical data was collected in six companies and was not representative of the industry sectors distribution. Furthermore, all the companies are from the same province in one country. Thus, the results cannot be generalized to the population of manufacturing SMEs.

This study could be extended with a survey of a larger samples of manufacturing SMEs. The theoretical model would need to be revised to include more contingency factors such as leadership style, organizational culture, and the influence of the owner. Furthermore, the measure of value would need to account for the perception of performance according to the owner.

## BIBLIOGRAPHY


Adolphs, P., & Epple, U. (2017, May 3). Status Report: Reference Architecture Model Industrie 4.0 (RAMI4.0). Retrieved May 3, 2017, from https://www.zvei.org/fileadmin/user_upload/Themen/Industrie_4.0/Das_Referenzarchitekturmodell_RAMI_4.0_und_die_Industrie_4.0-Komponente/pdf/5305_Publikation_GMA_Status_Report_ZVEI_Reference_Architecture_Model.pdf

Anderl, R., & Fleischer, J. (2015). *Guideline Industrie 4.0: Guiding principles for the implementation of Industrie 4.0 in small and medium sized businesses* (p. 30). VDMA Industries 4.0 forum. Retrieved from http://industrie40.vdma.org/documents/4214230/5356229/VDMA+Guideline+Industrie+40.pdf/cd1e8ef0-626e-432d-a2da-5c7a990b1a9b

Bagheri, B., Yang, S., Kao, H.-A., & Lee, J. (2015a). Cyber-physical systems architecture for self-aware machines in industry 4.0 environment. *IFAC-PapersOnLine*, *28*(3), 1622–1627. https://doi.org/10.1016/j.ifacol.2015.06.318

Bagheri, B., Yang, S., Kao, H.-A., & Lee, J. (2015b). Cyber-physical systems architecture for self-aware machines in industry 4.0 environment. *IFAC-PapersOnLine*, *28*(3), 1622–1627. https://doi.org/10.1016/j.ifacol.2015.06.318

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Bharadwaj, A. S. (2000). A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. *MIS Quarterly*, *24*(1), 169. https://doi.org/10.2307/3250983

Biswas, S., & Sen, J. (2016). A Proposed Architecture for Big Data Driven Supply Chain Analytics. *IUP Journal of Supply Chain Management*, *13*(3), 7–33. https://doi.org/10.2139/ssrn.2795884

Bordeleau, F.-E., Mosconi, E., & Santa-Eulalia, L. A. (2018). Business Intelligence in Industry 4.0: State of the art and research opportunities. In *Proceedings of the 51th Hawaii International Conference on System Sciences (HICSS)* (pp. 3944–3953). Waikoloa, Hawaii.

Brandenburger, J., Colla, V., Nastasi, G., Ferro, F., Schirm, C., & Melcher, J. (2016). Big Data Solution for Quality Monitoring and Improvement on Flat Steel Production. *IFAC-PapersOnLine*, *49*(20), 55–60. https://doi.org/10.1016/j.ifacol.2016.10.096

Cao, B., Wang, Z., Shi, H., & Yin, Y. (2015). Research and practice on Aluminum Industry 4.0 (pp. 517–521). Presented at the Proceedings of 6th International Conference on Intelligent Control and Information Processing, ICICIP 2015. https://doi.org/10.1109/ICICIP.2015.7388226

Chen, Y., Lee, G. M., Shu, L., & Crespi, N. (2016). Industrial internet of things-based collaborative sensing intelligence: Framework and research challenges. *Sensors (Switzerland)*, *16*(2). https://doi.org/10.3390/s16020215

Chen, Y.-J., Fan, C.-Y., & Chang, K.-H. (2016). Manufacturing intelligence for reducing false alarm of defect classification by integrating similarity matching approach in CMOS image sensor manufacturing. *Computers and Industrial Engineering*, *99*, 465–473. https://doi.org/10.1016/j.cie.2016.05.009

Chien, C.-F., Diaz, A. C., & Lan, Y.-B. (2014). A data mining approach for analyzing semiconductor MES and FDC data to enhance overall usage effectiveness (OUE). *International Journal of Computational Intelligence Systems*, *7*(SUPPL.2), 52–65. https://doi.org/10.1080/18756891.2014.947114

Chien, C.-F., Hsu, C.-Y., & Chen, P.-N. (2013a). Semiconductor fault detection and classification for yield enhancement and manufacturing intelligence. *Flexible Services and Manufacturing Journal*, *25*(3), 367–388. https://doi.org/10.1007/s10696-012-9161-4

Chien, C.-F., Hsu, S.-C., & Chen, Y.-J. (2013b). A system for online detection and classification of wafer bin map defect patterns for manufacturing intelligence. *International Journal of Production Research*, *51*(8), 2324–2338. https://doi.org/10.1080/00207543.2012.737943

Cocca, P., & Alberti, M. (2010). A framework to assess performance measurement systems in SMEs. *International Journal of Productivity and Performance Management*, *59*(2), 186–200. https://doi.org/10.1108/17410401011014258

Dai, Q., Zhong, R., Huang, G. Q., Qu, T., Zhang, T., & Luo, T. Y. (2012). Radio frequency identification-enabled real-time manufacturing execution system: a case study in an automotive part manufacturer. *International Journal of Computer Integrated Manufacturing*, *25*(1), 51–65. https://doi.org/10.1080/0951192x.2011.562546

Dews, F. (2017, January 12). 9 things to consider about U.S. manufacturing jobs | Brookings Institution. Retrieved January 28, 2017, from https://www.brookings.edu/blog/brookings-now/2017/01/12/9-things-to-consider-about-u-s-manufacturing-jobs/

Eckerson, W. (2011). *Performance Dashboards: Measuring, monitoring, and managing your business* (2nd ed.). Hoboken: John Wiley & Sons.

Eiskop, T., Snatkin, A., Kõrgesaar, K., & Søren, J. (2014). Development and application of a holistic production monitoring system. In *Proceedings of the International Conference of DAAAM Baltic "Industrial Engineering"* (Vol. 2014–January, pp. 85–91).

Elbashir, M. Z., Collier, P. A., & Davern, M. J. (2008). Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *International Journal of Accounting Information Systems*, *9*(3), 135–153. https://doi.org/10.1016/j.accinf.2008.03.001

Engeler, M., Treyer, D., Zogg, D., Wegener, K., & Kunz, A. (2016). Condition-based Maintenance: Model vs. Statistics a Performance Comparison. *Factories of the Future in the Digital Environment - Proceedings of the 49th CIRP Conference on Manufacturing Systems*, *57*, 253–258. https://doi.org/10.1016/j.procir.2016.11.044

Fink, L., Yogev, N., & Even, A. (2017). Business intelligence and organizational learning: An empirical investigation of value creation processes. *Information & Management*, *54*(1), 38–56. https://doi.org/10.1016/j.im.2016.03.009

Fleischmann, H., Kohl, J., & Franke, J. (2016). A Modular Architecture for the Design of Condition Monitoring Processes. *Factories of the Future in the Digital Environment - Proceedings of the 49th CIRP Conference on Manufacturing Systems*, *57*, 410–415. https://doi.org/10.1016/j.procir.2016.11.071

Fleischmann, H., Kohl, J., & Franke, J. (2016). A reference architecture for the development of socio-cyber-physical condition monitoring systems. Presented at the 2016 11th Systems of Systems Engineering Conference, SoSE 2016. https://doi.org/10.1109/SYSOSE.2016.7542963

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

Garengo, P., Biazzo, S., & Bititci, U. S. (2005). Performance measurement systems in SMEs: A review for a research agenda. *International Journal of Management Reviews*, *7*(1), 25–47. https://doi.org/10.1111/j.1468-2370.2005.00105.x

Garengo, P., & Bititci, U. (2007). Towards a contingency approach to performance measurement: an empirical study in Scottish SMEs. *International Journal of Operations & Production Management*, *27*(8), 802–825. https://doi.org/10.1108/01443570710763787

Gibbert, M., Ruigrok, W., & Wicki, B. (2008). What Passes as a Rigorous Case Study? *Strategic Management Journal*, *29*(13), 1465–1474. https://doi.org/10.1002/smj.722

Gröger, C., Kassner, L., Hoos, E., Königsberger, J., Kiefer, C., Silcher, S., & Mitschang, B. (2016). The data-driven factory leveraging big industrial data for agile, learning and human-centric manufacturing (Vol. 1, pp. 40–52). Presented at the ICEIS 2016 - Proceedings of the 18th International Conference on Enterprise Information Systems. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-84979608105&partnerID=40&md5=6f7cce3389807755b864e27576d6e627

Groger, C., & Stach, C. (2014). The mobile manufacturing dashboard (pp. 138–140). Presented at the 2014 IEEE International Conference on Pervasive Computing and Communication Workshops, PERCOM WORKSHOPS 2014. https://doi.org/10.1109/PerComW.2014.6815180

Hänel, T., & Felden, C. (2013). Operational Business Intelligence Meets Manufacturing. In *AMCIS 2013 Proceedings*.

Hänel, T., & Felden, C. (2016). Applying Operational Business Intelligence in production environments (pp. 365–377). Presented at the 25th International Conference on Information Systems Development, ISD 2016.

He, Z.-L., & Wong, P.-K. (2004). Exploration vs. Exploitation: An Empirical Test of the Ambidexterity Hypothesis. *Organization Science*, *15*(4), 481–494. https://doi.org/10.1287/orsc.1040.0078

Hvolby, H.-H., & Thorstenson, A. (2001). Indicators for performance measurement in small and medium-sized enterprises. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *215*(8), 1143–1146.

Institut de la statistique du Québec. (2013). *Portrait statistique du secteur manufacturier au Québec. Édition 2013 - manuf-portrait.pdf* (p. 109). Québec: Institut de la statistique du Québec. Retrieved from http://www.stat.gouv.qc.ca/statistiques/secteur-manufacturier/manuf-portrait.pdf

Jansen, J. J. P., Bosch, F. A. J. V. D., & Volberda, H. W. (2006). Exploratory Innovation, Exploitative Innovation, and Performance: Effects of Organizational Antecedents and Environmental Moderators. *Management Science*. https://doi.org/ttps://doi.org/10.1287/mnsc.1060.0576

Jansen, J. J. P., Tempelaar, M. P., van den Bosch, F. A. J., & Volberda, H. W. (2009). Structural Differentiation and Ambidexterity: The Mediating Role of Integration Mechanisms - orsc.1080.0415. *Organization Science*, *20*(4), 797–811. https://doi.org/10.1287/orsc.1080.0415

Kagermann, H., Wahlster, W., & Helbug, J. (2013). *Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0*. Berlin: Industrie 4.0 Working Group of Acatech.

Kao, Y.-T., Chang, S.-C., Dauzere-Peres, S., & Blue, J. (2016). Opportunity for improving fab effectiveness by predictive overall equipment effectiveness (POEE). Presented at the e-Manufacturing and Design Collaboration Symposium 2016, eMDC 2016 - Proceedings. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-84999028726&partnerID=40&md5=ccbaf4ddd33e9a69344614458932c253

Kaplan, R. S., & Norton, D. P. (1996). *The Balanced Scorecard: Translating strategy into action*. Boston, Massachusetts: Harvard Business Press.

Kassner, L. B., & Mitschang, B. (2015). MaXCept - Decision support in exception handling through unstructured data integration in the production context: An integral part of the smart factory (Vol. 2015–March, pp. 1007–1016). Presented at the Proceedings of the Annual Hawaii International Conference on System Sciences. https://doi.org/10.1109/HICSS.2015.124

Khaleel, H., Conzon, D., Kasinathan, P., Brizzi, P., Pastrone, C., Pramudianto, F., … Paralic, M. (2015). Heterogeneous applications, tools, and methodologies in the car manufacturing industry through an iot approach. *IEEE Systems Journal*, *PP*(99). https://doi.org/10.1109/JSYST.2015.2469681

Lee, C. K. M., Yeung, C. L., & Cheng, M. N. (2016). Research on IoT based Cyber Physical System for Industrial big data Analytics (Vol. 2016–January, pp. 1855–1859). Presented at the IEEE International Conference on Industrial Engineering and Engineering Management. https://doi.org/10.1109/IEEM.2015.7385969

Lee, H., Yoo, S., & Kim, Y.-W. (2016). An energy management framework for smart factory based on context-awareness (Vol. 2016–March, pp. 685–688). Presented at the International Conference on Advanced Communication Technology, ICACT. https://doi.org/10.1109/ICACT.2016.7423520

Lee, J., Bagheri, B., & Kao, H.-A. (2015). A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, *3*, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

Lee, J., Kao, H.-A., & Yang, S. (2014). Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment. *Product Services Systems and Value Creation. Proceedings of the 6th CIRP Conference on Industrial Product-Service Systems*, *16*, 3–8. https://doi.org/10.1016/j.procir.2014.02.001

Lee, R., Chen, I.-Y., & Nichols, P. (2016). A novel production process modeling for analytics. *International Journal of GEOMATE*, *11*(2), 2370–2377.

Leitão, P., Barbosa, J., Pereira, A., Barata, J., & Colombo, A. W. (2016). Specification of the PERFoRM architecture for the seamless production system reconfiguration (pp. 5729–5734). Presented at the IECON Proceedings (Industrial Electronics Conference). https://doi.org/10.1109/IECON.2016.7793007

Liao, Y., Deschamps, F., Loures, E. de F. R., & Ramos, L. F. P. (2017). Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. *International Journal of Production Research*, *55*(12), 3609–3629. https://doi.org/10.1080/00207543.2017.1308576

Lönnqvist, A., & Pirttimäki, V. (2006). The Measurement of Business Intelligence. *Information Systems Management*, *23*(1), 32–40. https://doi.org/10.1201/1078.10580530/45769.23.1.20061201/91770.4

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, *2*(1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information Technology and Organizational Performance: An Integrative Model of It Business Value. *MIS Q.*, *28*(2), 283–322. https://doi.org/10.2307/25148636

Ministère de l’Économie, de la Science et de l’Innovation. (2016). *Plan d’action en économie numérique* (pp. 1–78). Québec: Ministère de l’Économie, de la Science et de l’Innovation.

Miškuf, M., & Zolotová, I. (2015). Application of business intelligence solutions on manufacturing data (pp. 193–197). Presented at the SAMI 2015 - IEEE 13th International Symposium on Applied Machine Intelligence and Informatics, Proceedings. https://doi.org/10.1109/SAMI.2015.7061874

Neuböck, T., & Schrefl, M. (2015). Modelling knowledge about data analysis processes in manufacturing. *IFAC-PapersOnLine*, *28*(3), 277–282. https://doi.org/10.1016/j.ifacol.2015.06.094

Nino, M., Blanco, J. M., & Illarramendi, A. (2015). Business understanding, challenges and issues of Big Data Analytics for the servitization of a capital equipment manufacturer (pp. 1368–1377). Presented at the Proceedings - 2015 IEEE International Conference on Big Data, IEEE Big Data 2015. https://doi.org/10.1109/BigData.2015.7363897

*OECD SME and Entrepreneurship Outlook 2005*. (2005). OECD Publishing. https://doi.org/10.1787/9789264009257-en

Ojha, D., Acharya, C., & Cooper, D. (2018). Transformational leadership and supply chain ambidexterity: Mediating role of supply chain organizational learning and moderating role of uncertainty. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2018.01.001

Oneto, L., Anguita, D., Coraddu, A., Cleophas, T., & Xepapa, K. (2016). Vessel monitoring and design in industry 4.0: A data driven perspective. Presented at the 2016 IEEE 2nd International Forum on Research and Technologies for Society and Industry Leveraging a Better Tomorrow, RTSI 2016. https://doi.org/10.1109/RTSI.2016.7740594

Oses, N., Legarretaetxebarria, A., Quartulli, M., García, I., & Serrano, M. (2016). Uncertainty reduction in measuring and verification of energy savings by statistical learning in manufacturing environments. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *10*(3), 291–299. https://doi.org/10.1007/s12008-016-0302-y

Park, S. (2016). Development of Innovative Strategies for the Korean Manufacturing Industry by Use of the Connected Smart Factory (CSF). *Promoting Business Analytics and Quantitative Management of Technology: 4th International Conference on Information Technology and Quantitative Management (ITQM 2016)*, *91*, 744–750. https://doi.org/10.1016/j.procs.2016.07.067

Ravichandran, T., Lertwongsatien, C., & Lertwongsatien, C. (2005). Effect of Information Systems Resources and Capabilities on Firm Performance: A Resource-Based Perspective. *Journal of Management Information Systems*, *21*(4), 237–276. https://doi.org/10.1080/07421222.2005.11045820

Raymond, L., Marchand, M., St-Pierre, J., Cadieux, L., & Labelle, F. (2013). Dimensions of small business performance from the owner-manager's perspective: a re-conceptualization and empirical validation. *Entrepreneurship & Regional Development*, *25*(5–6), 468–499. https://doi.org/10.1080/08985626.2013.782344

Rix, M., Kujat, B., Meisen, T., & Jeschke, S. (2016). An Agile Information Processing Framework for High Pressure Die Casting Applications in Modern Manufacturing Systems. *Research and Innovation in Manufacturing: Key Enabling Technologies for the Factories of the Future - Proceedings of the 48th CIRP Conference on Manufacturing Systems*, *41*, 1084–1089. https://doi.org/10.1016/j.procir.2015.12.134

Ross, J., Beath, C. M., & Goodhue, D. L. (1996). Developing long-term competitiveness through information technology assets. *Sloan Management Review*, *38*(1), 31–42.

Schwab, K. (2016). *The fourth industrial revolution* (First U.S. edition). New York: Crown Business.

Shafiq, S. I., Velez, G., Toro, C., Sanin, C., & Szczerbicki, E. (2016). Designing Intelligent Factory: Conceptual Framework and Empirical Validation. *Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 20th International Conference KES-2016*, *96*, 1801–1808. https://doi.org/10.1016/j.procs.2016.09.351

STIQ. (2017). *Baromètre industriel québécois STIQ, 8e édition* (pp. 1–24). STIQ maillage industriel.

Taylor, A., & Taylor, M. (2014). Factors influencing effective implementation of performance measurement systems in small and medium-sized enterprises and large firms: a perspective from Contingency Theory. *International Journal of Production Research*, *52*(3), 847–866. https://doi.org/ttps://doi.org/10.1080/00207543.2013.842023

Tervonen, J., Isoherranen, V., & Heikkila, M. (2015). A review of the cognitive capabilities and data analysis issues of the future industrial Internet-of-Things (pp. 127–132). Presented at the 6th IEEE Conference on Cognitive Infocommunications, CogInfoCom 2015 - Proceedings. https://doi.org/10.1109/CogInfoCom.2015.7390577

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Wang, H., Osen, O. L., Li, G., Li, W., Dai, H.-N., & Zeng, W. (2016). Big data and industrial Internet of Things for the maritime industry in Northwestern Norway (Vol. 2016–January). Presented at the IEEE Region 10 Annual International Conference, Proceedings/TENCON. https://doi.org/10.1109/TENCON.2015.7372918

Wang, S., Wan, J., Li, D., & Zhang, C. (2016). Implementing Smart Factory of Industrie 4.0: An Outlook. *International Journal of Distributed Sensor Networks*, *2016*. https://doi.org/10.1155/2016/3159805

Wieland, M., Hirmer, P., Steimle, F., Gröger, C., Mitschang, B., Rehder, E., … Bauernhansl, T. (2016). Towards a Rule-based Manufacturing Integration Assistant.

*Factories of the Future in the Digital Environment - Proceedings of the 49th CIRP Conference on Manufacturing Systems*, *57*, 213–218.

Wuest, T., Irgens, C., & Thoben, K. (2014). An approach to monitoring quality in manufacturing using supervised machine learning on product state data. *Journal of Intelligent Manufacturing*, *25*(5), 1167–1180. https://doi.org/10.1007/s10845-013-0761-y

Xu, P., Mei, H., Ren, L., & Chen, W. (2017). ViDX: Visual Diagnostics of Assembly Line Performance in Smart Factories. *IEEE Transactions on Visualization and Computer Graphics*, *23*(1), 291–300. https://doi.org/10.1109/TVCG.2016.2598664

Yeoh, W., & Koronios, A. (2010). Critical Success Factors for Business Intelligence Systems. *Journal of Computer Information Systems*, *50*(3), 23–32. https://doi.org/10.1080/08874417.2010.11645404

Yin, R. K. (2009). *Case Study Research: Design and Methods*. SAGE. Retrieved from https://doi.org/10.4135/9781446260968

Yoon, J.-S., Shin, S.-J., & Suh, S.-H. (2012). A conceptual framework for the ubiquitous factory. *International Journal of Production Research*, *50*(8), 2174–2189.

Yu, H.-C., Lin, K.-Y., & Chien, C.-F. (2014). Hierarchical indices to detect equipment condition changes with high dimensional data for semiconductor manufacturing. *Journal of Intelligent Manufacturing*, *25*(5), 933–943. https://doi.org/10.1007/s10845-013-0785-3

Zhang, X., Peek, W. A., Pikas, B., & Lee, T. (2016). The Transformation and Upgrading of the Chinese Manufacturing Industry: Based on “German Industry 4.0.” *The Journal of Applied Business and Economics; Thunder Bay*, *18*(5), 97–105.

# APPENDIX A: PROOFS OF SUBMISSION

> Dear Elaine Mosconi -
>
> Congratulations!  We are happy to inform you that your paper
>
> Submission ID 327 - Business Intelligence in Industry 4.0: State of
> the art and research opportunities
>
> has been accepted to HICSS-51.
>
> You must now prepare the final version of your paper for publication.
> * Make sure that the format of your paper strictly follows the Final
> Format Specifications. (Step 6 in
> http://hicss.hawaii.edu/tracks-and-minitracks/authors/)
> * Include author name(s), affiliation(s), and email address(es), but no other major changes. Should you wish to add additional authors to your paper, you must seek approval from Track Chair(s) prior to final submission.
> * Submit your final paper to https://confs.precisionconference.com/~hicss51/ by September 22. The system will be available for the submission of final manuscripts on September 12, 6pm Hawaii time.
>
> Lastly, to secure publication in the Conference Proceedings, at least one author must register for the conference by October 1 and attend the conference to present the paper. Conference registration and hotel reservation information can be found at http://hicss.hawaii.edu/participants/.
>
> Sincerely,
> Alexander Pflaum, alexander.pflaum@uni-bamberg.de Chair, INTERNET AND
> THE DIGITAL ECONOMY - The Digital Supply Chain of the Future:
> Technologies, Applications and Business Models

ILS2018

International Conference on Information Systems, Logistics and Supply Chain

8-11 Jul 2018 Lyon (France)

Dear Fanny-Ãˆve Bordeleau,

Your submission has been uploaded for the conference "ILS 2018 - International Conference on Information Systems, Logistics and Supply Chain

The reference of your submission is:
Business Intelligence Value Creation: A Multiple Case Study in Manufacturing SMEs, F. Bordeleau [et al.] (sciencesconf.org:ils2018:183804)

Best Regards,
ils2018 team

https://ils2018.sciencesconf.org

# APPENDIX B: CONSENT FORMS

## FORMULAIRE D'INFORMATION ET DE CONSENTEMENT

Vous êtes invité(e) à participer à un projet de recherche. Le présent document vous renseigne sur les modalités de ce projet de recherche. S'il y a des mots ou des paragraphes que vous ne comprenez pas, n'hésitez pas à poser des questions. Pour participer à ce projet de recherche, vous devrez signer à la fin de ce document et nous vous en remettrons une copie signée et datée. Prenez tout le temps nécessaire pour prendre votre décision.

### Titre du projet de recherche

Les indicateurs de performance de l'industrie 4.0 : une étude empirique dans les manufacturiers québécois

### Personnes responsables du projet de recherche

Fanny-Ève Bordeleau, étudiante à la maîtrise en administration, Stratégie de l'intelligence d'affaires
Sous la codirection des professeurs Elaine Mosconi (Elaine.Mosconi@usherbrooke.ca) et
Luis Antonio de Santa Eulalia (L.Santa-Eulalia@USherbrooke.ca),
Département SIMQG
École de gestion, Université de Sherbrooke

### Financement du projet de recherche

La chercheuse a reçu des fonds de l'organisme subventionnaire Mitacs, ainsi que des fonds de Productique Québec pour mener à bien ce projet de recherche. Les fonds reçus couvrent les frais reliés à ce projet de recherche.

### Objectifs du projet de recherche

Cette recherche exploratoire a l'objectif général de comprendre quels facteurs liés aux technologies numériques et au suivi de la performance sont présents dans les entreprises manufacturières au Québec. On tentera d'établir une correspondance entre les indicateurs de performance utilisés par les manufacturiers québécois dans leurs fonctions de production et les indicateurs utilisés dans la littérature scientifique.

### Raison et nature de la participation

Votre participation à ce projet sera requise pour une entrevue d'environ 1 heure 30. Cette entrevue aura lieu à l'endroit qui vous convient, selon vos disponibilités. Vous aurez à répondre à des questions concernant les indicateurs de performance que votre entreprise utilise dans ses opérations de production ainsi que des questions sur des caractéristiques de votre entreprises liées à la gestion des technologies numériques.

Acceptez-vous que l'entrevue soit enregistrée ?

Oui ❒ Non ❒ Initiales du participant :_______________

**Avantages pouvant découler de la participation**

Vous ne retirerez aucun avantage direct à participer à ce projet de recherche. Cependant, votre participation aidera à mieux comprendre les mécanismes d'évaluation de la performance des technologies dans le cadre de l'industrie 4.0.

**Inconvénients et risques pouvant découler de la participation**

Votre participation à la recherche ne devrait pas comporter d'inconvénients significatifs, si ce n'est le fait de donner de votre temps. Vous pourrez demander de prendre une pause ou de poursuivre l'entrevue à un autre moment qui vous conviendra.

**Participation volontaire et possibilité de retrait**

Votre participation à ce projet de recherche est volontaire. Vous êtes donc libre de refuser d'y participer. Vous pouvez également vous retirer de ce projet à n'importe quel moment, sans avoir à donner de raisons, en informant l'équipe de recherche.

Advenant que vous vous retiriez de l'étude, demandez-vous que les documents audio ou écrits vous concernant soient détruits ?

Oui ❒ Non ❒ Initiales du participant :_______________

Il vous sera toujours possible de revenir sur votre décision. Le cas échéant, la chercheuse vous demandera explicitement si vous désirez la modifier.

**Compensation financière**

Vous ne recevrez pas de compensation financière pour votre participation à ce projet de recherche.

**Confidentialité, partage, surveillance et publications**

Durant votre participation à ce projet de recherche, la chercheuse responsable ainsi que les membres de son personnel de recherche recueilleront, dans un dossier de recherche, les renseignements vous concernant et nécessaires pour répondre aux objectifs scientifiques de ce projet de recherche.

Votre dossier de recherche peut comprendre des renseignements tels que votre nom, votre poste dans l'entreprise, votre ancienneté à ce poste, des enregistrements audio, ainsi que les réponses de toutes les entrevues qui seront réalisés dans le cadre du projet de recherche.

Tous les renseignements recueillis au cours du projet de recherche demeureront strictement confidentiels dans les limites prévues par la loi. Vous ne serez identifié que par un numéro de code. La clé du code reliant votre nom à votre dossier de recherche sera conservée par la chercheuse responsable de ce projet de recherche.
Les données recueillies seront conservées, sous clé, pendant au moins 5 ans par la chercheuse responsable aux fins exclusives du présent projet de recherche puis détruites.

Les données de recherche pourront être publiées ou faire l'objet de discussions scientifiques, mais il ne sera pas possible de vous identifier.

À des fins de surveillance et de contrôle, votre dossier de recherche pourrait être consulté par une personne mandatée par des organismes réglementaires, des représentants de l'établissement ou du comité d'éthique de la recherche. Ces personnes et ces organismes adhèrent à une politique de confidentialité.

Vous avez le droit de consulter votre dossier de recherche pour vérifier les renseignements recueillis et les faire rectifier au besoin.

**Résultats de la recherche**

Si vous souhaitez obtenir un résumé des résultats généraux de la recherche, veuillez indiquer une adresse où nous pourrons vous le faire parvenir :

Adresse électronique : ___________________________________________________

**Coordonnées de personnes-ressources**

Si vous avez des questions ou éprouvez des problèmes reliés au projet de recherche, ou si vous souhaitez vous en retirer, vous pouvez communiquer avec la chercheuse responsable ou avec un des directeurs de l'équipe de recherche aux numéros suivants :

Fanny-Ève Bordeleau (819) 679-6649
Elaine Mosconi (819) 821-8000 #63397
Luis Antonio de Santa-Eulalia (819) 821-8000 #65042

**Approbation par le comité d'éthique de la recherche**

Le Comité d'éthique de la recherche - Lettres et sciences humaines de l'Université de Sherbrooke a approuvé ce projet de recherche et en assurera le suivi. Pour toute question concernant vos droits en tant que participant à ce projet de recherche ou si vous avez des commentaires à formuler, vous pouvez communiquer avec ce comité au numéro de téléphone 819-821-8000 poste 62644 (ou sans frais au 1 800 267-8337) ou à l'adresse courriel cer_lsh@USherbrooke.ca.

**Signature de la personne participante**

J'ai pris connaissance du formulaire d'information et de consentement. On m'a expliqué le projet de recherche et le présent formulaire d'information et de consentement. On a répondu à mes questions et on m'a laissé le temps voulu pour prendre une décision. Après réflexion, je consens à participer à ce projet de recherche aux conditions qui y sont énoncées.

________________________________________________________________

Nom de la personne participante

________________________________________________________________

Signature                                                                                    Date

**Signature de la personne responsable de l'obtention du consentement**

J'ai expliqué au participant le projet de recherche et le présent formulaire d'information et de consentement et j'ai répondu aux questions qu'il m'a posées.

________________________________________________________________

Nom de la personne qui obtient le consentement

________________________________________________________________

Signature                                                                                    Date

**Engagement de la chercheuse responsable du projet de recherche**

Je certifie qu'on a expliqué à la personne participante le présent formulaire d'information et de consentement, que l'on a répondu aux questions qu'elle avait.

Je m'engage, avec l'équipe de recherche, à respecter ce qui a été convenu au formulaire d'information et de consentement et à en remettre une copie signée et datée à la personne participante.

________________________________________________________________

Nom de la chercheuse responsable

________________________________________________________________

Signature                                                                                    Date

# APPENDIX C: RESEARCH ETHICS COMMITTEE LETTER

UNIVERSITÉ DE SHERBROOKE

Sherbrooke, le 11 mai 2017

Mme Fanny-Ève Bordeleau
Étudiante
École de gestion
Université de Sherbrooke

**N/Réf. 2017-1476/Bordeleau**

**Objet : Approbation conditionnelle de votre projet de recherche**

Madame,

Le Comité d'éthique de la recherche – Lettres et sciences humaines a évalué votre projet de recherche intitulé **« Les indicateurs de performance de l'Industrie 4.0 : une étude empirique dans les manufacturiers québécois »** lors de sa réunion du 13 avril 2017.

Les documents suivants ont été analysés :

- Formulaire de demande initiale (F1-LSH)
- Projet de recherche (Guide d'entrevue-révision cér.pdf)
- Dépôt des documents (Lettre autorisation entreprise.pdf)
- Projet de recherche (Proposition de recherche-révision.pdf)
- Documents utilisés pour le recrutement (Courriel premier contact.pdf)
- Formulaire de consentement (Lettre consentement-révision.pdf)

Le comité vous informe que votre demande a été approuvée à l'unanimité, mais **conditionnellement** à la réception des clarifications ou modifications suivantes :

- La chercheuse mentionne qu'il n'y a aucun inconvénient pour les personnes participantes. Toutefois, il faudrait mentionner l'inconvénient lié au temps consacré pour participer aux entretiens semi-dirigés.

- Concernant le formulaire de consentement, le comité demande de :

  • Harmoniser le titre dans le formulaire de consentement avec celui du projet. En effet, le titre n'inclut pas le sous-titre présent dans le projet : « une étude empirique dans les manufacturiers québécois »;
  • Ajouter une question explicite pour demander aux personnes participantes si elles acceptent l'enregistrement de l'entrevue;
  • Harmoniser l'objectif de la recherche avec celui présenté dans la description du projet. En effet, l'objectif du projet de recherche tel que décrit dans le formulaire de consentement ne semble pas correspondre exactement à l'objectif de la recherche, puisqu'on n'y fait pas référence aux technologies numériques et à leur lien avec les indicateurs de performance. Par exemple, on pourrait mentionner « L'objectif général est de comprendre quels facteurs liés aux technologies numériques et au suivi de la performance sont présents dans les entreprises manufacturières au Québec ».

- Le comité vous recommande de prévoir un courriel d'invitation qui ressemble un peu moins au formulaire de consentement, de façon à le rendre plus attrayant. Par exemple, on pourrait revoir la phrase suivante : « Votre participation à la recherche ne devrait pas comporter d'inconvénients significatifs, si ce n'est le fait de donner de votre temps » qui est peut-être trop formelle. Par ailleurs, le courriel pourrait souligner davantage ce que la participation pourrait apporter plutôt que mentionner uniquement les contraintes. Enfin, il serait utile de mentionner au début du courriel que c'est la firme Productique Québec qui a fourni leurs coordonnées.

Vous devez transmettre vos réponses via le formulaire 20 (Formulaire - réponses aux conditions) par Nagano. Vos réponses et les modifications apportées à votre demande feront l'objet d'une évaluation dès leur réception. Si elles sont jugées satisfaisantes, le comité vous fera parvenir une lettre d'approbation finale dans Nagano.

Nous vous rappelons que vous ne pouvez pas commencer le recrutement des personnes participantes et la collecte des données avant d'avoir reçu l'approbation finale du projet.

Le comité vous remercie d'avoir porté cette demande d'approbation à son attention et vous prie de recevoir, Madame, ses salutations distinguées.

Olivier Laverdière
Président du CÉR - Lettres et sciences humaines
Professeur au département de psychologie
Faculté des lettres et sciences humaines

c. c. Vice-décanat à la recherche
Directeur ou directrice de recherche (le cas échéant)
Service d'appui à la recherche, à l'innovation et à la création (le cas échéant)

# APPENDIX D: CASE STUDY PROTOCOL

Table 21. Case study protocol Based on Yin (2009)

| | |
|---|---|
| **A** | Introduction to the case study and purpose of protocol |
| **1.** | Case study questions and propositions |
| **RQ** | How do the factors relating to BI&A business value creation vary in manufacturing SMEs in the context of Industry 4.0, compared to earlier literature? |
| **P1a and b** | Alignment between senior management and IT is a necessary condition for (a) operation BI&A capabilities and (b) strategic BI&A capabilities in manufacturing SME. |
| **P2 a and b** | A competent and business aware BI&A team is a necessary condition for (a) operation BI&A capabilities and (b) strategic BI&A capabilities in manufacturing SME. |
| **P3 a and b** | A performant and available BI&A technical infrastructure is a necessary condition for (a) operation BI&A capabilities and (b) strategic BI&A capabilities in manufacturing SME. |
| **P4 a and b** | Having good operational BI&A capabilities is a necessary condition for (a) operational and (b) strategic business value in manufacturing SME. |
| **P5** | Having good strategic BI&A capabilities is a necessary condition for strategic business value in manufacturing SME. |
| **P6** | Generating operational value through BI&A is a necessary condition for strategic business value in manufacturing SME. |
| **P7** | The link between resources and capabilities is moderated by a high organizational learning ambidexterity. |
| | Controls variables (number of employees, annual revenues, industrial domain and location, owner role) do not explain value creation through data utilization in manufacturing SME. |
| **2.** | Theoretical framework and logic model |
| | See section 2 |
| **3.** | Role of protocol |
| | The role of this protocol is ensuring a standard method for all cases and guide data analysis and reporting. |
| **B.** | Data collection procedures |
| **1.** | Names of sites to be visited, including contact persons (CONFIDENTIAL) |
| **2.** | Data collection plan |
| | Internal documents related to Industry 4.0 and digital transformation, including strategic plan and previous digital maturity assessment (if available) |
| | Semi-structured interviews with an executive manager, based on the case study propositions (see interview guide); includes structured questions and open-ended discussions. |
| | Plant tour; tour notes |
| **3.** | Expected preparation prior to data collection |
| | Request document and permission to use them, request permission to take notes |
| | Have consent forms ready to sign, request permission to register the interview, have a blank interview guide to take notes |
| **C.** | Outline of case-study report |
| | Cross-case analysis without individual case presentation organized linearly following structure of propositions |
| | Preserve anonymity of SME and respondents as requested by studied SME and considering potentially strategic information revealed during study |
| | Have the respondent and SME board of directors revise the manuscript before publication to ensure their statements are properly reported |

| | |
|---|---|
| **D.** | Case study questions |
| **SM** | Does senior management of the SME understand and are they applying data and digital governance? Is senior management involved in the technological projects? Are senior management and the technical team aligned on the technological orientations and technology role in supporting strategic objectives? |
| **BT** | Is the SME supported by a performant, knowledgeable and business oriented technical team? |
| **IN** | Does the SME have a performant and useful to their needs technological infrastructure? |
| **OC** | What are the SME's operational capabilities? Are they taking advantage of real-time production data? |
| **SC** | What are the SME's strategic capabilities? Are strategic decisions and strategic planning data driven? |
| **AMB** | What is the organizational learning mode in the SME? Does it influence the way resources are utilized? |
| **OV** | Is the SME creating operational value from its data? Does is look like this value creation could be explained by the studied variables? |
| **SV** | Is the SME creating strategic value from its data? Does is look like this value creation could be explained by the studied variables? |
| **PerfInd** | What are the most commonly used performance indicators for manufacturing operations? Are the indicators used in practice the same as the most cited in academic literature? Are performance indicators refreshed or compiled frequently enough in practice to be useful? Can they be considered viable measures of business value? |
| **Vision** | What was the SME's motivation to engage in a digital transformation or Industry 4.0 action plan? What are the expected outcomes? |
| **E.** | Outline of data analysis |
| | Qualitative analysis of tour notes and internal documents |
| | Qualitative analysis of interviews (semi and non-structured part) |
| | Coding of structured questions' answers and pattern detection if possible |
| | Corrections and adjustments to the structured questionnaire |

Table 22. Themes of the interview, part 1

| |
|---|
| **External environment:** industrial sector, description, competition and trends |
| **Internal environment and governance**: last year's annual sales, sales variations, total number of employees, interviewee position and seniority, company's vision, mission and values, governance structure |
| **Business activities**: typical customer, customer issues, typical product, production issues, strategic planning frequency, content, usefulness |
| **Business technologies**: technical teams (IT and BI), leadership of these teams, types of BI/ data valorization activities, data and digital governance activities |
| **Future:** interest for digital transformation, next big digital projects |
| **Operational performance measurement**: use of performance indicators, is your company monitoring the following indicators? How often are they refreshed? Do you feel this frequency is adequate? Are there any other performance indicators you feel are critical to monitoring of operations? Of technological project success? How do you consider performance indicators as measures of operations performance? Are they sufficient? |
| Conformity rate or quality rate |
| Utilization rate or up time |
| Productivity |

| |
|---|
| Production effectiveness |
| Overall equipment effectiveness (OEE) |
| Production yield |
| Technological projects return on investment (ROI) |
| Production costs |
| Energy consumption |
| Inventory levels |
| Time to market |

# APPENDIX E: INTERVIEW QUESTIONNAIRE

Table 23. Questionnaire items, interview part 2

| | |
|---|---|
| **Senior management and IT alignment (SM)** | |
| SM1 | Senior management forms a steering committee for major digital data-related projects. |
| SM2 | Senior management and technical staff agree on business objectives. |
| SM3 | Senior management is involved in establishing technological priorities. |
| SM4 | Standards are enforced when choosing a data valorization solution. |
| SM5 | The company's technological data valorization infrastructure is defined. |
| **BI&A team (BT)** | |
| BT1 | Operations (non-technical) staff is assuming leadership of data valorization projects. |
| Technical staff… | |
| BT2 | Has the technical skills to do their jobs. |
| BT3 | Offer technical support to users. |
| BT4 | Is staying up to date in their technical knowledge. |
| BT5 | Is looking to solve business problems. |
| BT6 | Is looking to discover business opportunities. |
| **BI&A technical infrastructure (IN)** | |
| IN1 | Users have access to data they need. |
| Data valorization technologies in the company… | |
| IN2 | Are performant. |
| IN3 | Are responding quickly. |
| IN4 | Are interrelated. |
| IN5 | Are useful. |
| IN6 | Are easy to use. |
| **Operational BI&A capabilities (OC)** | |
| OC1 | Operations are supported by digital data valorization technologies. |
| OC2 | Operational decisions are data-driven. |
| OC3 | Data analysis is embedded in operations. |
| OC4 | Information and data is digitalized throughout the company. |
| OC5 | Operational data is analyzed in real time. |
| OC6 | Data is used to model processes. |
| OC7 | Data is used to optimize processes. |
| **Strategic BI&A capabilities (SC)** | |
| Information coming from data valorization activities… | |
| SC1 | Offers a complete view of the company's situation. |
| SC2 | Enables a complete company's situation analysis. |
| SC3 | Enables an analysis of trends, threats and opportunities. |
| SC4 | Is used when establishing the company's strategy. |
| SC5 | Is used to evaluate the company's business model. |
| SC6 | Contributes to establishing the need for a digital transformation. |
| **BI&A operational business value (OV)** | |
| Since your company started undertaking data valorization activities, … | |
| OV1 | Internal processes are more time-efficient. |
| OV2 | Internal processes are more cost efficient. |
| OV3 | Productivity is higher. |
| OV4 | Inventory levels are lower. |

| | |
|---|---|
| OV5 | Operation costs are lower. |
| OV6 | Clients' satisfaction is higher. |
| OV7 | Time to market is lower. |
| OV8 | Conformity rate is higher. |
| OV9 | Utilization rate is higher. |
| OV10 | Process effectiveness is higher. |
| **BI&A strategic business value (SV)** | |
| Since your company started undertaking data valorization activities, … | |
| SV1 | Revenues are increasing. |
| SV2 | Markets shares are increasing. |
| SV3 | Profits are increasing. |
| SV4 | The company is achieving more business objectives. |
| SV5 | The company is reacting better to changes in environment. |
| SV6 | The company is reacting better to competitors' activities. |
| SV7 | The company has a better understanding of customers' needs. |
| SV8 | The company is making better business decisions. |
| **Organizational learning ambidexterity: exploration (ER)** | |
| ER1 | Company accepts customer requests outside of existing products or services portfolio. |
| ER2 | Company is developing new products or services. |
| ER3 | Company is testing new products in known markets before release. |
| ER4 | Company is actively looking for new markets. |
| ER5 | Company is actively looking for new distribution channels. |
| ER6 | Company is actively looking for new clients. |
| **Organizational learning ambidexterity: exploitation (ET)** | |
| ET1 | Existing products and services portfolio is revised on a regular basis. |
| ET2 | Small regular updates of existing products and services are released. |
| ET3 | Resources are deployed to develop existing markets. |
| ET4 | Decreasing processes' internal costs is a critical objective. |
| ET5 | Resources are developed to improve existing processes. |
| ET6 | Service portfolio is expanded for existing clients. |